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(57) Abstract

Techniques predict transaction costs in filling an order by one or more trades on an exchange. Data indicating past transactions on an exchange are received. Measurements of transaction price and transaction volume and transaction time are derived from the data. A predicted price return for a time period is computed based on the measurements. Then a predicted transaction cost is computed in response to the predicted price return, for use in deciding whether to trade and for use in scheduling trades.

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TECHNIQUES FOR MEASURING TRANSACTION COSTS AND SCHEDULING TRADES ON AN EXCHANGE

CROSS REFERENCE TO RELATED APPLICATION

This application claims priority to a provisional application entitled COMPUTER TECHNIQUES FOR SCHEDULING TRANSACTIONS by inventors Stuart Gould, Berry Cox, Brendan Wootten, Tim Sargent, Ed Tom, Todd Hurtubise and Anthony Centrella (Attorney Docket No. 44497-371) filed February 5, 1999, which application is incorporated herein in its entirety by reference.

FIELD OF THE INVENTION

The present invention relates to trading on an exchange and more particularly to techniques for measurement and prediction of trade impact costs on total transaction costs required to execute a buy or sell order in equity markets.

BACKGROUND OF THE INVENTION

Any item can be traded on an exchange. Securities, currencies and commodities are different kinds of fungible items traded on well known exchanges. For example, the New York Stock Exchange or the National Association of Securities Dealers Automated Quotations system (NASDAQ) are exchanges established for trading corporate securities.

A dealer may maintain an inventory of a fungible item, such as stocks in a given corporation. The dealer may sell from that inventory to buyers, and buy from sellers to augment that inventory. The dealer buys the item at a bid price announced on the exchange. The dealer sells the item at an ask price also announced on the exchange. A quote refers to either the ask price or the bid price for a particular item by the dealer. Typically, there is an amount of the item, such as a number of shares of a corporate security, called the quote depth associated with the quote.

An individual dealer will maintain a difference, called a bid-ask spread, or simply "spread," between the ask price and the bid price at any instant of time. The dealer's ask price will be higher than that dealer's bid price at the same instant, so that the dealer can cover the dealer's costs and make a profit on each pair of buy and sell transactions the dealer participates in. The dealer will vary the bid and ask price over time to accommodate the supply and demand for the item.

A market for a given item, such as stock in a given corporation, may include several dealers in that item -- all posting their bid and ask prices for that item on the exchange. Sellers will seek out the dealer with the highest bid price on the exchange; and, buyers will seek out the dealer with the lowest ask price. The market bid price is the highest bid price on the exchange at a given instant, and the market ask price is the lowest ask price on the exchange at that instant. In general the market also maintains a spread, with an instantaneous market bid price lower than the instantaneous market ask price.

From the perspective of a trader buying or selling from the market, as soon as a trade is made, i.e., an item on such an exchange is bought or an item is sold to a dealer, the trader suffers a shortfall. This is because the buying trader can only sell back the stock at that moment for the lower bid price, and the selling trader can only buy back that item for the higher ask price. The buying trader relies on the market bid price increasing with time after the purchase, while the selling trader relies on the market ask price dropping with time after the sale. This shortfall is not absorbed until the trade is followed by the complementary trade (i.e., the purchase is followed by a sale, or the sale is followed by a purchase), so at the time of the initial trade only half the spread is considered sunk by the trader in the shortfall.

Hereinafter, a trader will refer to a person who decides to buy or sell an item on an exchange, whether for the trader's own benefit or for the benefit of another, and whether or not the trader actually interacts directly with the exchange.

When the trader decides to trade, the trader anticipates a shortfall of about half the spread at the time of the decision. However, because the market prices may move between the decision to trade and the actual trade, the shortfall experienced when the trade is implemented (the implementation shortfall) includes the effects of the market movement. The combination of the half spread at the decision time and the movement in market prices is called the execution cost. A given trade can experience greater or lesser execution costs depending on the timing and size of the trade for reasons that will be described more later. In addition, the trader is in the hole by any commissions and taxes charged to execute the trade. These costs include commissions by brokers or other agents, transfer taxes, Securities and Exchange Commission (SEC) fees, and other administrative costs of securities trades through the markets or exchanges. Finally, if the trader backs out of the trade so that there are no execution costs or commissions or taxes, there may still be one or more opportunity costs, such as the interest lost by taking the money for a cancelled purchase out of an interest bearing account and then not investing it immediately. The implementation shortfall (IS) can be represented by Equation 1A.

$$IS = CT + EC + OC \qquad (1A)$$

where CT represents the costs of commissions and taxes, EC represents the execution costs, and OC represents the opportunity costs. The IS of Equation 1 also represents the transaction costs of the trade on the exchange.

The market price changes that contribute to the execution costs (EC) include price changes due to trades of others, the trend cost (TC), and price changes due to the trade the trader makes, the impact cost (IC). Considering the IC and TC, Equation 1 becomes Equation 1B:

$$IS = CT + BA / 2 + IC + TC + OC \qquad (1B)$$

where BA represents the bid-ask spread at the time the decision to trade is made.

When a trader decides to make a trade, that decision is better if the trader considers not just BA (the instantaneous spread at the time of the decision) but rather considers the entire expected implementation shortfall, E{IS}. However, the size of IS is difficult to predict with current methods because the various terms in Equation 1, especially the impact cost (IC) and trend cost (TC) are difficult to predict.

Most transaction cost forecasting models focus only on impact costs. Trend costs are either ignored or dismissed through diversification arguments. Other treatments justify excluding trend costs because they cancel out over time. However, this assumption of zero trend cost is only valid for two trading scenarios. The first scenario leading to zero trend cost involves market orders that are executed immediately after the decision to trade. The second scenario leading to zero trend costs involve well-diversified, two-sided program trades. Other trading scenarios can expect to suffer real trend costs. For example, trend costs can be suffered by trades conducted as working orders, volume weighted average price (VWAP) trades, limit orders, and manager transitions. One reason that trend costs are typically ignored in transaction costs forecasts is that short-term price forecasts are needed that are difficult and challenging to provide.

One popular estimation technique called an "inventory risk" method attempts to forecast impact cost by predicting a dealer's cost to clear an order. This cost is derived by examining the order size relative to the average volume (e.g., the one day trading volume, the five days trading volume, and the 10 days trading volume). Using this measure of time, a risk premium is established using a stock's historic volatility. Volatility is a measure of the size of price fluctuations known in the art, such as the standard deviation of daily price changes observed over a large number of days. Exclusive use of volatility to estimate price movement abandons an attempt to forecast direction. This technique then fails to account for the significant impact that order direction, relative to price momentum, has on transaction costs.

What is needed is an improved prediction of terms that contribute to the transaction costs, especially the impact and trend costs. In addition techniques are needed to utilize this information in managing a portfolio of items traded on an exchange. In particular, techniques are needed to use estimates of IC and TC for scheduling the time and amount of items to trade in response to a customer order to buy or sell items on an exchange.

SUMMARY OF THE INVENTION

The foregoing needs, and other features and advantages that will become apparent from the following description, are achieved by the methods, apparatuses, computer program products and systems of the present invention. In one aspect a component of transaction cost is measured. In another aspect a component is used to build a model predicting that component of transaction cost. In another aspect a model is used to predict transaction cost. The measured or predicted transaction costs or its components are used to schedule trading on the exchange that reduces or minimizes cost to the trader.

According to one aspect of the invention, techniques predict transaction costs in filling an order by one or more trades on an exchange. The order has an order size for a particular item. Measurements of transaction price transaction volume and transaction time are selected. A model for price is fit to the selected measurements. The model includes a term of the form βV^{δ} wherein V is a function of volume. Values for β and δ αρε δετερμινεδ. A predicted impact cost for a trade is computed in response to βS^{δ} where S is responsive to a transaction size for the trade.

According to another aspect of the invention, techniques predict transaction costs in filling an order by one or more trades on an exchange. The order has an order size for a particular item. Data indicating transactions on an exchange are received. Measurements of transaction price and transaction volume and transaction time are derived from the data. A predicted price return for a time period is computed based on the measurements. A predicted transaction cost is computed in response to the predicted price return.

According to another aspect of the invention, techniques predict transaction costs in filling an order by one or more trades on an exchange. The order has an order size for a particular item. Data are received indicating transactions on an exchange. Measurements of transaction price and transaction volume and transaction time are derived from the data. A predicted impact cost and a predicted trend cost are computed based on the measurements. A predicted transaction cost is then computed in response to the predicted trend cost and the predicted impact cost.

According to another aspect of the invention, techniques derive transaction costs of trades on an exchange directly from measurements. Data indicating transactions on the exchange are received. Measurements including a transaction price, a transaction volume, and a transaction time for each of a plurality of transactions are derived from the data. An impact cost and a trend cost are derived from the measurements. A transaction cost is computed in response to the trend cost and the impact cost.

According to another aspect of the invention, techniques derive impact costs of trades on an exchange directly from measurements. Measurements of transaction price and transaction volume and transaction time are selected. The selected measurements are ordered temporally. It is determined whether a current transaction is part of a particular trade for which impact costs are to be measured. If a current transaction is part of the particular trade, then if a price difference from an immediately preceding transaction is in the same direction as the current transaction an impact equal to the price difference is associated with the current transaction. If the current transaction is a last transaction in the particular trade, the impact cost is computed as the volume weighted average of the impacts associated with the transaction from the particular trade.

According to another aspect of the invention, a decision aid system predicts transaction costs in filling an order for a particular item by one or more trades on an exchange. The order has an order size. The system includes a network and a computer readable medium connected to the network. One or more processors connected to the network receive data over the network indicating transactions on the exchange. The processors derive measurements of transaction price and transaction volume and transaction time and compute a predicted price return for a time period based on the selected measurements. Then the processors compute a predicted transaction cost in response to the predicted price return.

BRIEF DESCRIPTION OF THE DRAWINGS

The present invention is illustrated by way of example, and not by way of limitation, in the figures of the accompanying drawings and in which like reference numerals refer to similar elements and in which:

Figure 1 is a flow chart showing a method for predicting transaction costs for use in executing trades on an exchange according to one embodiment of the present invention.

Figure 2 is a block diagram that illustrates a computer system 200 upon which an embodiment of the invention may be implemented.

Figures 3A to 3E depict a method for measuring impact costs directly from these data according to another embodiment of this invention.

Figure 4A illustrates a method for formulating an impact model to fit against the data according to one embodiment of the present invention.

Figure 4B shows an exemplary report generated as a result of fitting the impact cost model to data according to one embodiment.

Figure 5A shows the M Function which plots liquidity against a signed percentage change in price, used by an embodiment of the present invention.

Figure 5B is flow chart for formulating a price return model according to another embodiment of the present invention.

Figure 5C and 5D depict left and right portions of an exemplary report generated as a result of fitting the price return model to data according to an embodiment of the invention.

Figure 6A and 6B depict the left and right portions of an example report for a sample portfolio trade.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

Techniques for forecasting transaction costs and scheduling trades on an exchange are described. In the following description, for the purposes of explanation, numerous specific details are set forth in order to provide a thorough understanding of the present invention. It will be apparent, however, to one skilled in the art that the present invention may be practiced without these specific details. In other instances, well-known structures and devices are shown in block diagram form in order to avoid unnecessarily obscuring the present invention.

FUNCTIONAL OVERVIEW

Figure 1 is a flow chart showing a method for predicting transaction costs for use in executing trades on an exchange according to one embodiment of the present invention. As will be described in more detail below, the history of market behavior is used to measure a relationship between price return and trading volume in step 110. Price changes are posted on the exchange in short times called ticks. The price return is the accumulated price change over a period longer than individual ticks, such as periods of a half hour, or an hour, or a day. In step 120, the measurements are divided into categories. One category is for measurements obtained while most of the trading volume in the period was associated with a decrease in price. Another category is for measurements obtained while most of the trading volume was associated with an increase in price. In step 130 each set of measurements is fit by a separate model of a form such as given by Equation 2.

$$\frac{\Delta P}{P} = \alpha + \beta V^{\delta}. \qquad (2)$$

where P is price, ΔP is price changes, and V is signed volume. The model's parameters include at least β and δ which are adjusted in ways known in the art to obtain some degree of agreement with the measurements in the category being fit The parameters can be constants for the sliding window or can themselves be estimated using other relationships described by other equations, as will be shown in more detail below.

Once the parameters of the model have been obtained, they can be used with the size of a proposed trade to predict impact cost, by substituting the proposed trade size or a quantity derived from it for the signed volume in step 140. This substitution assumes that the proposed trade will influence prices in the same way that net signed volume affects returns for the period.

In step 150, the impact cost is used to compute the transaction cost such as by computing and adding a trend cost to the other terms contributing to the implementation shortfall given by Equation 1B. In step 160 a trade is executed in response to the transaction cost. For example, if the transaction cost is acceptable, the trade may be executed as proposed. If the transaction cost is unacceptable, the trade may be cancelled or the order refused. Figure 1 also shows that a different trade can be proposed and the impact cost can be recomputed for the new proposed trade, as shown by the arrow directed up from step 150 into step 140. This path may be taken if the proposed trade has an unacceptable transaction cost, but other ways of implementing a buy or sell order can be considered.

This embodiment estimates separate models for each item traded on the exchange. This approach provides more accuracy than purely cross sectional models because model parameters can vary dramatically across items, such as across different securities traded on the NASDAQ system. In some embodiments cross-sectional variables are also included in the model. The partitioning of models between periods of positive and negative signed volumes, or into other categories, allows for asymmetric price responses to buy and sell orders. More details for the steps shown in Figure 1 are described in later sections.

HARDWARE OVERVIEW

Figure 2 is a block diagram that illustrates a computer system 200 upon which an embodiment of the invention may be implemented. Computer system 200 includes a bus 202 or other communication mechanism for communicating information, and a processor 204

coupled with bus 202 for processing information. Computer system 200 also includes a main memory 206, such as a random access memory (RAM) or other dynamic storage device, coupled to bus 202 for storing information and instructions to be executed by processor 204. Main memory 206 also may be used for storing temporary variables or other intermediate information during execution of instructions to be executed by processor 204. Computer system 200 further includes a read only memory (ROM) 208 or other static storage device coupled to bus 202 for storing static information and instructions for processor 204. A storage device 210, such as a magnetic disk or optical disk, is provided and coupled to bus 202 for storing information and instructions.

Computer system 200 may be coupled via bus 202 to a display 212, such as a cathode ray tube (CRT), for displaying information to a computer user. An input device 214, including alphanumeric and other keys, is coupled to bus 202 for communicating information and command selections to processor 204. Another type of user input device is cursor control 216, such as a mouse, a trackball, or cursor direction keys for communicating direction information and command selections to processor 204 and for controlling cursor movement on display 212. This input device typically has two degrees of freedom in two axes, a first axis (e.g., x) and a second axis (e.g., y), that allows the device to specify positions in a plane.

The invention is related to the use of computer system 200 for obtaining measurements and predicting impact costs and transaction costs. According to some embodiments of the invention, a forecast report or trade is provided by computer system 200 in response to processor 204 executing one or more sequences of one or more instructions contained in main memory 206. Such instructions may be read into main memory 206 from another computer-readable medium, such as storage device 210. Execution of the sequences of instructions contained in main memory 206 causes processor 204 to perform the process steps described herein. In alternative embodiments, hard-wired circuitry may be used in

place of or in combination with software instructions to implement the invention. Thus, embodiments of the invention are not limited to any specific combination of hardware circuitry and software.

The term "computer-readable medium" as used herein refers to any medium that participates in providing instructions to processor 204 for execution. Such a medium may take many forms, including but not limited to, non-volatile media, volatile media, and transmission media. Non-volatile media includes, for example, optical or magnetic disks, such as storage device 210. Volatile media includes dynamic memory, such as main memory 206. Transmission media includes coaxial cables, copper wire and fiber optics, including the wires that comprise bus 202. Transmission media can also take the form of acoustic or light waves, such as those generated during radio-wave and infra-red data communications.

Common forms of computer-readable media include, for example, a floppy disk, a flexible disk, hard disk, magnetic tape, or any other magnetic medium, a CD-ROM, any other optical medium, punchcards, papertape, any other physical medium with patterns of holes, a RAM, a PROM, and EPROM, a FLASH-EPROM, any other memory chip or cartridge, a carrier wave as described hereinafter, or any other medium from which a computer can read.

Various forms of computer readable media may be involved in carrying one or more sequences of one or more instructions to processor 204 for execution. For example, the instructions may initially be carried on a magnetic disk of a remote computer. The remote computer can load the instructions into its dynamic memory and send the instructions over a telephone line using a modem. A modem local to computer system 200 can receive the data on the telephone line and use an infra-red transmitter to convert the data to an infra-red signal. An infra-red detector can receive the data carried in the infra-red signal and appropriate circuitry can place the data on bus 202. Bus 202 carries the data to main memory 206, from which processor 204 retrieves and executes the instructions. The instructions

received by main memory 206 may optionally be stored on storage device 210 either before or after execution by processor 204.

Computer system 200 also includes a communication interface 218 coupled to bus 202. Communication interface 218 provides a two-way data communication coupling to a network link 220 that is connected to a local network 222. For example, communication interface 218 may be an integrated services digital network (ISDN) card or a modem to provide a data communication connection to a corresponding type of telephone line. As another example, communication interface 218 may be a local area network (LAN) card to provide a data communication connection to a compatible LAN. Wireless links may also be implemented. In any such implementation, communication interface 218 sends and receives electrical, electromagnetic or optical signals that carry digital data streams representing various types of information.

Network link 220 typically provides data communication through one or more networks to other data devices. For example, network link 220 may provide a connection through local network 222 to a host computer 224 or to data equipment operated by an Internet Service Provider (ISP) 226. ISP 226 in turn provides data communication services through the world wide packet data communication network now commonly referred to as the "Internet" 228. Local network 222 and Internet 228 both use electrical, electromagnetic or optical signals that carry digital data streams. The signals through the various networks and the signals on network link 220 and through communication interface 218, which carry the digital data to and from computer system 200, are exemplary forms of carrier waves transporting the information.

Computer system 200 can send messages and receive data, including program code, through the network(s), network link 220 and communication interface 218. In the Internet example, a server 230 might transmit a requested code for an application program through Internet 228, ISP 226, local network 222 and communication interface 218. In accordance

with the invention, one such downloaded application provides for forecast computation as described herein.

The received code may be executed by processor 204 as it is received, and/or stored in storage device 210, or other non-volatile storage for later execution. In this manner, computer system 200 may obtain application code in the form of a carrier wave.

DERIVING MEASUREMENTS FROM HISTORICAL TRADING DATA

The methods and techniques employed here utilize historical trading data available from the exchange to form models and predict impact or trend costs or transaction costs or any combination of these. One form of the data comprises a stream of trade records, such as the data on a tape available from FITCH DATA SERVICES™ containing every trade in every stock in the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), NASDAQ National Market System, and NASDAQ SmallCap Market. Other data include proprietary trade data of the trader, such as the execution records of the trader's own program trade system.

In one embodiment, the Fitch data are filtered iteratively four times to sample a subset of all the transactions and time stamp the transactions. For each filtered transaction, the data stream includes trade price, trade volume, trade direction (upticks and downticks), and execution times.

To obtain the measurements required by step 110 of Figure 1, these data are segregated by stock. For a given duration time period for which the model is designed, say one half hour, the price return on the stock is computed. In one embodiment, the last price in each period is subtracted from the last price in the next period. Similarly, the signed volume is obtained for each period by adding all the uptick volumes and subtracting all the downtick volumes in each period.

A sliding window indicates which half hour periods make up the data set to be used in the models. In one embodiment, the sliding window is 20 days long which provides 260 half

hour periods with observations. In this embodiment, the window slides by 5 days, which means that, after five days have passed, the model coefficients are re-estimated for the 20 day window ending five days after the previous window ended.

Figures 3A to 3E depict a method for measuring impact costs directly from these data according to another embodiment of this invention.

In step 310 of Figure 3A all the transactions in the filtered data from the time a particular trade was initiated until the last transaction of that particular trade is executed are ordered temporally. A first transaction in this time interval is then the current transaction under consideration. All transactions in this interval of time are either associated with the particular trade or with other trades. If the current transaction is part of the particular trade, as tested in step 320 then in step 325 the difference is computed between the price of that current transaction and the price of the immediately previous transaction. If there is no previous transaction then the quote price when the trade was initiated is used as the price of the immediately previous transaction. In step 330, this price difference is tested to see if it is in the same direction as the transaction impact direction (which is upward for a buy and downward for a sale). If the price difference from the immediately previous transaction to the current transaction of the particular trade is in the same direction, then the impact associated with the current transaction is equal to this price difference. The flow then skips to step 360 in which it is determined whether the current transaction is the last transaction to consider for this particular trade. If the time of the current transaction is before the time of the last transaction of a particular trade, then the current transaction is not the last one. In this case, the next transaction becomes the current transaction and flow returns to step 320.

On the other hand, if the current transaction is not part of the particular trade when tested at step 320, flow transfers to step 340 which handles the case of the current transaction not being a part of the particular trade. In this case, the difference in price is computed between the current transaction and the price of each prior transaction that is part of the

particular trade. In step 350 it is determined whether this price difference is in the opposite direction to the transaction impact that is, down for buy or up for sell. If the price difference is in the opposite direction and the magnitude of the price difference is greater than the impact associated with the prior transaction of the particular trade, then the impact associated with that prior transaction is reset to zero. That is, the prior transaction does not contribute to the overall impact costs of the particular trade. Steps 340 and 350 are repeated for every transaction that is prior to the current transaction and is a transaction associated with the particular trade. Once a After all prior transactions of the particular trade have been compared, flow goes to step 360 which determines if the current transaction is the last one the next transaction is made current at step 365, and then or not. If the current transaction is not the last one, flow control passes back to step 320. If the current transaction is the last one in the interval of the particular trade then flow passes to step 370. In step 370, the impact costs of the particular trade is computed as the volume weighted average of the impact of the transactions of the particular trade. Note that the impacts of certain transactions of the particular trade may have been set to zero in step 350. In this way measured impact cost per unit of traded item will either be positive or zero.

Figures 3B to 3E are graphs showing price changes with execution time of buys. The buy transactions associated with a particular trade are shown as filled vertical bars and transaction associated with other trades are shown as unfilled vertical bars.

Following the method of directly measuring the impact costs illustrated in Figure 3A, the impact costs can be computed for this situation illustrated in Figure 3B. In Figure 3B, only the transaction T2 is associated with the particular trade. The other transactions T1 and T3-T7 are transactions associated with trades by others and do not contribute to the impact costs of our trade. These transactions are ordered by time as required by step 310. When our trade was initiated the asked price was 47. The first transaction in the time interval is T1 which is not our trade that is not part of the particular trade as used in Figure 3A. Therefore

control skips to step 340 where the difference is computed between T1 and all the other prior transactions of the particular trade. There are no such prior transactions of the particular trade and flows goes to step 360 which determines whether this is the last transaction within the time interval of the particular trade. T1 is not the final transaction. Therefore flow goes to step 365 where T2 is made the current transaction before passing control to step 320. In step 320 it is determined that T2 is part of the particular trade and therefore the price difference is computed between transaction T2 and transaction T1 in step 325. That difference is +1 because the price at transaction T2 is greater than the price at transaction 1. Since these transactions are buy transactions and the difference is an upward change in price, the price difference is in the same direction as the transaction impact expected from a buy so the impact associated with transaction T2 is set equal to this price difference of +1. Flow now goes to step 360 which determines that this is the last transaction of the particular trade. Flow then goes to step 370 where the impact cost of the particular trade is computed from the volume weighted average of the impact of all the transactions associated with the trade. That volume weighted average is 1, the impact of the only transaction associated with the trade, transaction T1.

Figure 3C shows this same transactions as shown in Figure 3B except that transaction T4 is now considered part of the particular trade. In this case, the processing of transactions T1 and T2 are identical to that described above for Figure 3B. The next transaction would be transaction T3 which is not part of the particular trade. Therefore, the price of T3 will be compared to the price of all prior transactions that are part of the trade according to step 340. The difference between the price of transaction T3 and that of transaction T2 is not opposite in direction to what is expected from a buy and therefore the impact associated with transaction T2 is not reset to 0. In a sense, the impact of transaction T2 is still embedded in the price of transaction T3. The next transaction, T4, is part of the particular trade so flow goes to step 325. The price difference with the immediately proceeding transaction T3 is +2.

This is in the same direction as the transaction impact expected for a buy so the impact associated with transaction T4 is +2. Flow then goes to 360 where it is determined that this is the last transaction of the trade. Flow then goes to 370 where the impact costs of the trade is computed as the volume weighted average of the impacts of the transactions of this particular trade. Assuming the volume associated with transaction T2 and the volume associated with transaction T4 are the same, the total impact of the two transactions is 3, 1 from transaction T2 and 2 from transaction T4. The impact cost per unit volume is then the average, i.e. 3/2.

Figure 3D shows buy transactions similar to Figure 3C. Thus, transaction T2 has associated an impact of 1 and transaction T4 has a impact associated with it of 2. The price does not change for transaction T5 so that does not affect the impact costs. When transaction T6 is considered, flow goes to step 340 because transaction T6 is not part of the particular trade. Here the difference between transaction T6 and transaction T4, the prior transaction that is part of the trade, is -2. As tested in step 350, this is opposite to the direction of the transition impact expected from a buy. This difference of -2 is equal in magnitude to the impact associated with transaction T4 of +2. Therefore, it satisfies the requirements of step 350 to reset the impact associated with transaction T4 to 0. In a sense, the impact cost of transaction T4 is no longer embedded in the price at transaction T6. Steps 340 and 350 would repeat for all prior transactions that are part of the trade. In this case, when the prior set of transactions T6 is compared to the price of transaction T2, the conditions are not satisfied to reset the impact of T2 to 0. Therefore, transaction T2 retains its impact of 1. When transaction T7 is encountered by the method, since transaction T7 is part of a particular trade, its price is compared to the price of the immediately proceeding transaction T6. The difference is +1 so the impact associated with transaction T7 is +1. T7 is the last transaction within the time interval of this particular trade so flow goes to step 370 where the impact costs of the trade for unit volume is computed. Assuming all transactions of this trade have equal volume, the impact cost for unit volume is 1 associated with transaction T2, 0

associated with transaction T4 and 1 associated with transaction T7. Thus, the volume weighted average is 2/3.

Figure 3E is similar to Figure 3D through transaction T4. However, after the transaction T6 the impacts of both transactions T2 and T4 of this particular trade are reset to 0. In a sense, no impact costs are embedded any longer in the price affecting transaction T6. Transaction T7 of the particular trade does not differ from the price of transaction T6 therefore T7 has an impact of 0. Thus the impact costs of the trade in Figure 3E is 0.

Trend costs can be computed from the above measured impact cost and the deviation of the actual trade execution cost (EC) from the midpoint of the bid and ask price, i.e. the bid/ask midpoint (BAM) according to Equation 3. Note that (TP-BAM) is the actual execution cost. Thus

$$TC = \frac{TS}{|TS|} * (TP - BAM) - IC - BA/2 \qquad (3)$$

Recall TS is the trade size. In equation 3, TS is positive for a buy and negative for a sell.

CATEGORIES OF MEASUREMENTS

According to several embodiments, after the measurements are obtained, they are segregated into two or more categories as shown in step 120 of Figure 1. Preferably the categories are defined depending on market price movement during the period of each measurement. This is done to reflect the asymmetric dynamics expected of market price movements in rising and falling markets.

In one embodiment only two categories are defined. Into one category fall all measurements for which the net signed volume of the period is positive, i.e. for which most of the traded volume was associated with price rises. In the other are placed all measurements in which the signed volume for the period is negative, i.e., most of the volume traded occurred with price decreases.

THE IMPACT COST MODELS

Different embodiments use different models related to a basic model of the form given by Equation 2, above. If the data includes total price return, then Equation 2 has the advantage of the α term which accounts for variables that affect prices but are unrelated to order volume or order flow. Such variables measure buying or selling pressures not fully captured by signed volume.

If the data consist of directly measured impact costs, then the α term can be dropped and a model of the form of Equation 4 can be used with the data.

$$\frac{\Delta P}{P} = \beta V^{\delta}. \qquad (4)$$

FITTING THE IMPACT COST MODEL TO THE DATA

In various embodiments a model is fit to the measurements in a sliding window by adjusting the parameters of the model, such as α, β and δ. Model fitting procedures known in the art and amenable for this step include linear regression, joint estimation techniques, and maximum likelihood methods.

The length of the sliding window, or model estimation period, is varied to balance competing considerations. The purpose is to detect the relationship between price variations and volume variations, e.g., a stock's liquidity, that is stable enough to have predictive power at times later than the sliding window, i.e. that is valid "out-of-sample" as well as in sample. If the length of the sliding window is too long, liquidity shifts won't register quickly enough. If the length is too short, fleeting changes and noise in price-volume patterns likely will create unstable estimates of the model parameters and unstable predictions of liquidity. The length or duration of the sliding window must be adjusted to produce values of β and δ that

remain insulated from random noise, while remaining sensitive to patterns that persist out of sample.

In some embodiments, the model parameters are considered to be constant for the duration of the sliding window. In one of these embodiments the sliding window has a duration of 20 days which provides 260 half-hour observations. Every five days the window in this embodiment slides five days and the model parameters are estimated again. The model parameters are then used to predict liquidity for data outside the sliding window. This schedule provides reasonably accurate performance as indicated by the statistical property R^2 known in the art. R^2 is related to the percent of the squared variations of data about its mean value that are accounted for by the model. For example, for the 30 days between October 1, 1998 and November 12, 1998, the model predicted 22% of the variations in the out-of-sample data.

In other embodiments, the values of α and β and δ are allowed to depend on other variables within the window, and thus are not constant in the window. The significance of this approach is that it allows the model to attempt to account for more of the variability left unexplained by the use of constant coefficients, and it allows the model to be more realistic. It is observed that identical orders can generate very different price responses, and that such responses depend on market conditions such as volatility and quote depth. As stated earlier, quote depth is the amount of an item associated with a bid price or an ask price. Volatility is a measure of the variations of a variable, for example, as estimated by the standard deviation of a sample of data for the variable. These embodiments seek to discover variables with which α or β or δ vary systematically so that the forecasting accuracy can be improved by making these parameters functions of such variables. This embodiment is illustrated in Figure 4.

Based on risk-return calculations from the perspective of the counterparties to a trade, a pool of candidate variables are identified, as shown by step 410 in Figure 4. For a given

item, β or δ will change whenever there are changes in the counterparty's expected risk-adjusted return on the trade. Based on this analysis, the candidate variables are expected to fall into one of five classes.

One class of candidate variables are those that cause changes in required risk adjusted return. The counterparty increases the risk adjusted return required on trades; and impact costs will be greater for both buy and sale orders. A second class of candidate variables are those that cause changes in expected price trend. If a counterparty expect prices to rise even higher, impact costs for buy orders will increase, but impact costs for sell orders will decrease. The third class of candidate variables are those that effect changes in expected impact costs. If the counterparty expects impact costs to rise when the counterparty makes the complementary trade to unwind the position, impact costs will rise for the initiating buy and sell orders. The fourth class of candidate variables are those that effect changes in expected price volatility. If the counterparty expects prices to become more volatile, impact costs will rise for both buy and sell orders. The fifth class of candidate variables are those which cause changes in expected impact costs volatility. The counterparty expect future impact costs to become more volatile; and impact costs on the initiating trades will rise for both buy and sell orders.

The changes in expected impact costs involve variables that measure the depth and liquidity of the market for the amount of an item, such as for the stock's shares. Increases in the values of these variables (except for decrease in bid ask spreads) raise expected risk adjusted returns by lowering expected liquidation costs. In effect, these variables affect the counterparty's expected impact costs when closing the position for both buy and sell side models. These variables should have negative coefficients. These candidate variables include quote depth, trade frequency, average trade size, trend in bid ask spread, and trend in volume.

Other candidate variables effect changes in expected impact costs volatility. These variables measure the volatility of market liquidity. Increases in these variables lower

expected risk adjusted returns by widening the distribution of future liquidation costs. As liquidity becomes more volatile - increasing the downside risk of impact costs - chances increase that a counterparty will have to unwind at a material loss. For both buy side and sell side models, these variables should have positive coefficients. These variables include volatility of quote depth, volatility of trade frequency, volatility of trade size, volatility of big-ask spreads and volatility of dollar volume. Candidate variables that effect changes in expected price trends affect expected returns by changing expected liquidation prices. When the trend and initial order are in opposite directions, impact costs will fall since counterparties will expect to unwind at a greater profit. When the trend and initial order are in the same direction, impact costs will rise as counterparties demand greater spreads to offset adverse price movements. These variables include price return in previous half-hour, divergences: signed volume and returns, divergences: block and non-block assigned volume, and RSI of signed volume in last half-hour.

Variables that effect changes in expected price trend volatility affect expected returns because higher price volatility lowers expected risk adjusted returns by widening the distribution of future liquidation costs. There is greater risk that the counterparty will liquidate at a material loss. These variables should have positive coefficients in both the buy and sell side models. These variables include tick-by-tick price volatility, price volatility of the difference between high and low prices divided by the average price, and price volatility of last half-hour return.

These and other variables deduced by similar arguments are used to establish a pool of candidate variables as required by step 410 in Figure 4. In step 420, the candidate variables are tested to find significant relationships with price movement. In step 430, the candidate variables are tested to find multiplicative variables that show significant relationship with prices proportional to order volume. These are variables that effect β. In step 440, the candidate variables are tested to find exponential variables that show significant relationship

with the logarithm of process to the logarithm of order volume. These are variables that affect δ.

For example, in one embodiment, candidate variables found to significantly contribute to β include the liquidity variables of trades per minute during interval, shares traded per minute, average time between trades and average trade size. Also significant were the liquidity risk variables of standard deviation of time between trades and coefficient of trade frequency variation. The price trend risk variables found significant include tick-by-tick price volatility, volatility in the difference between high and low price divided by average for the interval, and volatility in last half-hour return. These variables then contribute as multiplicative variables according to step 430 in Figure 4.

In general, if X1 through Xp represent variables that affect prices but are unrelated to order flow, and Y1 through Yq represent variables that affect the mutiplicative price response to order flow, and Z1 through Zr represent variables that affect the exponential price response to order flow, then

$$\alpha = a1*X1 + a2*X2 + \ldots + ap*Xp \tag{5A}$$

$$\beta = b1*Y1 + b2*Y2 + \ldots + bq*Yq \tag{5B}$$

and

$$\delta = c1*Z1 + c2*Z2 + \ldots +cr*Zr \tag{5C}$$

Once the variables are selected and evaluated from the data, the coefficients a1 through ap, b1 though bq and c1 through cr are estimated, as indicated by step 450 in Figure 4. In the preferred embodiment, these coefficients can be estimated directly using maximum likelihood techniques, as is known in the art. For example, the likelihood function L given by Equation 5D for one embodiment is maximized.

$$L = \prod_{i=1}^{n}\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)\times\exp\left(\frac{1}{-2\sigma^2}\left(Y_i - \hat{Y}_i\right)^2\right) \tag{5D}$$

where L = Likelihood Function; Y = Actual Impact Cost (LHS); $\hat{Y}$ = Model Forecast for Impact Cost = Ax+Bm×V^C; σ^2 = Variance of Impact Cost Model Errors; and n = Number of Observations in Estimation.

Alternatively, the problem can be linearized by taking the logarithm and ignoring the variability caused by the X variables to obtain a least squares estimate of the b and c coefficients. Then the predicted value of the volume terms can be generated using the b and c coefficients, and the residual variability fit in a second stage linear regression to solve for the a coefficients.

In one embodiment, the variables are selected and their coefficients are computed every five days as the sliding window slides. The values of the variables based on the most recent and previous periods are then used with the constant coefficients based on the sliding window to estimate β and δ at the present time. These values of β and δ are then used to predict impact cost for the next half hour period as shown by step 460 in Figure 4. For this purpose, it is preferred to fit the variables in step 450 to price change data in a following period when the coefficients are calculated in the sliding window.

In another embodiment, direct estimates of pre-trade impact are derived by regressing short-term returns against signed trade volume. Derive direct estimates of pre- trade impact by regress-ing short- term returns against signed trade volumes. For example, for each 1/ 2 hour interval over a 10 day period, the 1/ 2 hour return regressed against (1) the square root of the dollar volume on upticks, and (2) the square root of the dollar volume on downticks. Using the S& P 1500 as our universe, the median results for this two factor regression were as follows:

Table 1A

	Median Beta	Median Tstat
Constant Term	-.0527	-.228
Square Root Uptick Volume	.0037	5.16
Square Root Downtick Volume	.0031	-4.24
Median Model R^2 26%		

Table 1B

Differences in Impact Cost of Uptick Volume (Buy Orders)		
S&P Industry Sector	**Sector Median Beta**	**Sector Median Tstat**
Constant Cyclicals	.0056	9.50
Transportation	.0055	3.87
Capital Goods	.0054	7.66
Basic Industry	.0052	5.97
SAMPLE MEDIAN	.0037	5.16
Health Care	.0036	4.46
Technology	.0029	4.14
Consumer Staple	.0025	3.36
Energy	.0024	1.66
Communications	.0020	1.05
Financials	.0017	2.28
Utilities	.0016	1.67

Table 1C

Differences in Impact Cost of Downtick Volume (Sell Orders)		
S&P Industry Sector	**Sector Median Beta**	**Sector Median Tstat**
Basic Industry	-.0050	-6.39
Consumer Cyclicals	-.0048	-9.15
Capital Goods	-.0039	-6.11
Transportation	-.0035	-2.77
SAMPLE MEDIAN	-.0031	-4.24
Health Care	-.0028	-3.83
Communications	-.0026	-1.48
Consumer Staple	-.0025	-3.64
Technology	-.0020	-3.16
Energy	-.0020	-1.59
Utilities	-.0017	-1.94
Financials	-.0014	-2.04

PREDICTING IMPACT COSTS

Once the parameters of the model have been obtained, they can be used with the size of a proposed trade to estimate an impact cost, by substituting the proposed trade size or a quantity derived from size for the signed volume in step 140. This substitution assumes that the proposed trade will influence prices in the same way that net signed volume affects returns for the period, such the half hour period of the example.

IMPACT COSTS WITH PREDICTED PRICE TRENDS

In other embodiments, impact cost models are developed based on predictions of price trends. The direct measurement of impact costs show that both impact costs and transaction costs are affected by price trends. For example, impact costs were measured directly in a sample of over 106,000 transactions in response to over 38,000 orders from August 1997 to April 1998, as shown in Table 2A. The results are shown in Tables 2B and 2C.

Table 2A

Description of Transaction Sample			
Statistic	Buys	Sells	All
Number of Clients	46	46	53
Number of Programs	492	288	776
Number of Stocks	2,187	2,205	2,649
Number of Orders	25,642	12,712	38,354
Number of Executions	57,033	49,285	106,318
Number of Shares	55 Mil	52 Mil	107 Mil
Earliest Execution	08/29/97	08/29/97	08/29/97
Last Execution	04/13/98	04/13/98	04/13/98

Table 2B

Transaction Cost Component	Sample Means ($ Per Share)		
	Buy Orders	**Sell Orders**	**All Orders**
Commissions	.037	.036	.036
Half-Spread	.064	.063	.064
Impact Costs	.051	.050	.050
Trend Costs	.001	.064	.031
Total	0.153	0.213	0.181
Abs Value of Trend	.274	.339	.305

Table 2C

Transaction Cost Component	Standard Devisions ($ Per Share)		
	Buy Orders	**Sell Orders**	**All Orders**
Commissions	.012	.011	.012
Half-Spread	.062	0.61	.062
Impact Costs	.089	.072	.084
Trend Costs	.348	.414	.371
Total			
Abs Value of Trend Costs	.284	.343	.305

The total transaction costs depicted on the fifth line of Table 2B generally confirms the findings of other studies: buy orders cost approximately 15 cents per share, and sell orders average 21 cents per share. These data also indicate that impact cost of buying and selling stocks is roughly the same at 5 cents per share. Trend costs for buy orders average to zero over time. For sell orders, trend costs average 6 centers per share. These trend costs make selling stocks forty percent more expensive than buying stocks. The asymmetry is therefore

an issue of timing, not liquidity. Because managers tend to sell together, prices often move before the order of any one manager can be executed. In down trends, the higher frequency of seller initiated trades increases trend costs for sell orders of all sizes. Trend costs often dominate impact cost by a factor of five or six. In nearly ninety percent of individual orders, the absolute value of trend costs exceeds 5 cents per share. In fifty percent of orders, trend costs are at least five times the size of impact costs.

Though managers can reduce trend costs by trading diversified or two-sided programs, diversification at the program level is no substitute for informed trading using stocks specific trend costs estimates. Trend costs could cancel entirely, but in a way that erases the expected gain of every stock in the program. The correlation between short-term price trend and the gain motivating the trade determines whether trend costs will diversify away benignly or, instead systematically consume the gain that the manager is attempting to capture.

The relationship between impact cost and price trend is shown in this data by the M Function which plots liquidity against a signed percentage change in price, as shown in Figure 5. Liquidity is defined as the volume change divided by the absolute value of the change in price. Impact costs are related to the change in price due to a change in volume. Thus liquidity and impact cost vary inversely, though not proportionately; as liquidity increases, impact costs decrease. Thus the relationship between liquidity and price change shown in figure 5, indicates that a relationship between impact cost and price trend is expected.

In region A of Figure 5, large price changes are associated with relatively low volume. This occurs when new information leads to a quick and uniform shift in the perception of fair

value for an item. In this case, prices can move significantly on relatively low volume. During such information driven price trends, opinions move in concert and liquidity is diminished. At the limit of no volume, bid and ask prices gap higher or lower. This region is characterized by high volatility as large price swings are expected.

In region B of Figure 5, there is uncertainty about fair value, such as when traders react differently to new information. Liquidity rises as differing opinions register is strong but balanced order flows. During such periods, impact costs are low for both buy and sell orders.

In region C of Figure 5, prices are near equilibrium as perceptions of fair value are stable across market participants. The item's trading range, e.g., the spread, will narrow. Liquidity is low because the volume decreases as the motivation to trade diminishes.

Given these relationships, a model for transaction costs is formed which depends on the direction and magnitude of the price trend. Expected impact costs will be higher when the price trend is greater, as in region A of the M Function shown in Figure 5. At these times volatility is higher and volume is lower. Expected impact costs depends on direction of the price trend because buying into a downtrend carries lower impact costs than buying into an uptrend, even when the order size is identical. When the trade and the trend are in opposite directions, impact costs are lower. The observations summarized in Tables 2A, 2B and 2C indicate that trend costs have an important effect on overall transaction costs. This effect is due to the influence of price trend on both trend cost and impact cost.

In one embodiment in which the data are segregated into three categories, the change in price per change in volume is determined for each stock in each category. Then this quantity is multiplied by the change in volume. In this embodiment the volume that has an

impact cost is only the excess volume over the quote depth. Thus if the order has an order size, OS, the excess volume, S, is the order size minus the prevailing quote depth. For buy orders, OS = S - offer size; and for sell orders, OS = S - bid size. Note that in this convention OS and S are positive for buy orders and negative for sell orders. The model impact costs then has the form of Equation 6.

$$IC_x = |S| * \frac{\partial P}{\partial V_x} \qquad (6)$$

where the subscript x indicates the term is derived for data in category x, where x = u (uptrend), d (downtrend) or n (neutral).

TRANSACTION COSTS WITH PRICE TRENDS

The effect of price trend on the trend cost is straightforward, given a forecast of price return (ΔPrice) over the next period of time, and is expressed by Equation 7.

$$TC = S * \Delta Price \qquad (7)$$

ΔPrice is positive for uptrends, negative for downtrends, and zero for neutral trends. TC is negative (good) when S and ΔPrice have opposite signs.

The mix of impact and trend costs on total transaction cost depends on how the trades are scheduled. If the trader can be patient, the order can be parceled out over time, thereby minimizing impact costs. However, the longer the price is exposed to market pressures, the greater its potential move away from the level at trade initiation. This price drift increases the magnitude of TC, which is a cost when TC is negative and a benefit when TC is positive. If the order is urgent, the trader can fill the entire order immediately at market. Trend costs will be minimal because the price has little time to move. However, impact costs will be maximal because the price must change enough to induce sufficient trades to fill the order immediately. The relative importance of impact and trend costs can be assigned quantitatively using a trade urgency quotient, λ. This urgency quotient λ ranges from 0 to 1.

If $\lambda = 1$, the trade is a market order that is executed immediately, regardless of impact. If $\lambda = 0$, the trade is parceled out so all trades are within the prevailing quote depth, irrespective of the time needed to fill the order.

When predicting impact and trend costs, it is not known whether the market will rise or fall or remain neutral during the transactions. Given a probability Px that the future price return will be in category x, where x = u (uptrend), d (downtrend) or n (neutral) the expected, predicted impact and trend costs can be written according to Equation 8.

$$\begin{aligned} \text{IC-TC} = \quad & Pu * [\lambda * \{|S| * \partial P/\partial Vu\} + (1-\lambda)*(S*\Delta Price)\ ] \\ & - Pn * [\lambda * \{|S| * \partial P/\partial Vn\} + 0\ ] \\ & - Pd * [\lambda * \{|S| * \partial P/\partial Vd\} + (1-\lambda)*(S*\Delta Price)\ ] \end{aligned} \tag{8}$$

The transaction cost (T) is then given by the above terms added to a negative of the commission cost (CT) and half the product of the order size and the bid ask spread (BA) assuming no opportunity costs given by Equation 9.

$$\begin{aligned} T = -IS = -CT - [|OS|*(BA / 2)] & - Pu * [\lambda * \{|S| * \partial P/\partial Vu\} + (1-\lambda)*(S*\Delta Price)\ ] \\ & - Pn * [\lambda * \{|S| * \partial P/\partial Vn\} + 0\ ] \\ & - Pd * [\lambda * \{|S| * \partial P/\partial Vd\} + (1-\lambda)*(S*\Delta Price)\ ] \end{aligned} \tag{9}$$

This bid ask spread (BA) is a positive quantity determined from the ask price minus the bid price prevailing when the trader initiates the order. The midpoint of the bid and ask prices range is the benchmark for the paper trade in the implementation shortfall methodology.

Equation 9 requires estimates for the probability of up, down, and neutral trends, a forecast of price return (ΔPrice) and a forecast of price elasticity (inverse liquidity) $\partial P/\partial V$ in up, down and neutral markets.

FORECASTING RETURNS

In one embodiment, the price trend probabilities, Pu, Pd, and Pn, are computed based on the one day volatility estimate σ derived over the last 90 daily returns. Pu is the fraction of those 90 daily returns with returns greater than $+0.75\sigma$. Pd is the fraction of those 90 daily

returns with returns less than -0.75σ. Pn is the fraction of those 90 daily returns with returns between -0.75σ and +0.75σ.

In one embodiment, the forecast of liquidity $(\partial P/\partial Vx)^{-1}$ like β is based on another pool of predictive variables. Daily liquidity is defined as the daily volume divided by the 90 day average volume divided by the absolute percentage price change. For example, five classes of variables were predictive for the 1,500 stocks in the S&P Supercomposite over 80 days in the fourth quarter. Those classes were:

(1) market capitalization and institutional popularity;

(2) short-term volume trends;

(3) price and volume volatility;

(4) changes in price volatility; and

(5) contemporaneous returns.

Table 3A lists the variables found predictive in this example and explains the relationship. Table 3B gives the regression results for this example. Note that these variables include some cross-sectional variables involving industry and exchange associated with the stock.

Table 3A

Explanatory Variable	LHS Variable: (Daily Volume/90 Day Average Volume) ÷Absolute Value of 1 Day Return			
	No Contemporaneous Returns Variables		Perfect Forecast of Tomorrow's Return	
	T Statistics	Variance Inflation Factor	T Statistics	Variance Inflation Factor
Intercept	5.2	0.0	16.2	0.0
Log of market Capitalization	22.5	1.8	19.7	1.8
10 Day Volume Trend Score	22.0	1.0	28.7	1.0
90 Day Return Volatility	-12.8	3.1	-26.7	3.2
90 Day Volume Volatility	-10.2	1.7	-10.1	1.7
10 Day Average Turnover- 90 Day Avg Turnover	19.9	1.2	19.8	1.6
10 Day Average (High-Low)/Close	-11.2	3.1	-3.7	3.2
10 Day (H-L)/C Std Dev - 90 Day (H-L)/C Std Dev	4.5	1.5	2.8	1.5
Dummy Variable for NYSE Listed Stocks	8.9	1.4	6.7	1.4
1 Day Contemporaneous Return			11.4	2.0
Dummy Variable for 1 Day Return>.75σ			-76.4	1.4
Dummy Variable for 1 Day Return <.75σ			-74.3	1.5
Number of Observations in Sample	110,567		110,567	
Adjusted R^2	4.2		15.7	
1500 Stocks for 100 Days: 11/08/96-01/02-1997				

Table 3B

Explanatory Variable	Predictive Relationship
Last Trade vs. Closing Bid-Ask Spread	When closing bid rises to the level of the last trade price, this positive momentum often carries prices higher the next day. Conversely, when the closing ask falls to the level of the last trade, next day returns are often negative.
Industry Relative Returns	When stocks have outperformed or underperformed their industry over the previous week, these stocks tend to reverse the following day: Overbought outperformers fall in price, and oversold losers snap back to the upside.
14 Day Relative Strength Indicator	After controlling for industry relative returns (see above), stocks display short-term momentum. This positive serial correlation can be modeled with RSIs, oscillators or other trend momentum indicators. We use the 14 Day RSI.
Beta Adjusted Industry Returns	Industry portfolios show short-term momentum, whereas individual stocks exhibit short-term reversal. After controlling for these reversal effects, positive (negative) industry momentum is bullish(bearish) for the individual stocks in the industry.
RSI Overbought/Oversold Levels	In a multivariate context, the venerable RSI trading rules actually display the effect technicians have long claimed for this indicator. Stocks with RSIs over 80 often correct to the downside, and those with RSIs over 20 often reverse to the upside.
1/5 Day Volume Oscillator	When today's volume is high relative to the volume over the previous week, it is bullish for tomorrow's returns. When today's volume is low relative to the previous week's volume, it has bearish implications for tomorrow's returns.
Close-Low/High-Low	Stocks show a pronounced intraday reversal effect. When a stock closes at the bottom of its intraday trading range, it is bullish for tomorrow's returns. Conversely, when the last trade is near the high in a wide intraday range, it is a bearish sign.

In preferred embodiments, predicting returns comprises six steps as shown in Figure 5B. In step 501, a pool of candidate variables is built. In step 502, the best subset of variables is identified for each item for which price return is to be forecast. In step 503, the variables are selected for the final models. In step 504, weights are determined for the selected

variables. In step 505, the model is run to generate real-time forecasts. In step 506, the forecasting accuracy out of sample is monitored to indicate improvements required in earlier steps such as step 501, 503 and 504.

In step 501, the pool of candidate indicators contains all the variables that may be included in the individual forecasting models. Because system overhead is proportional to pool size, indicators must meet strict performance criteria before inclusion. The indicator's forecasting power must be stable across time and significant for many stocks. To identify the best subset for a given stock in step 502, each indicator's ability to forecast the stock's half-hour returns is tested. Inclusion in the subset is based on three criteria: (1) overall directional accuracy -- the ability to forecast up and down moves; (2) directional accuracy for *big* moves; and (3) statistical significance (t statistic or Chi^2). Many variables in the best subset capture the same predicative relationships. To keep the multivariate models parisimonious -- and thereby minimize problems of overfitting and multi-collinearity -- the final models only include variables that make incremental and significant independent contributions to forecasting power in step 503.

In step 504 two forecasting models are used for each stock, a least squares model (OLS) and an ordered probit model (PROBIT) known in the art. Each model assigns weights to the predictor variables using different objective functions. The OLS model minimizes the sum of squared differences. The PROBIT model maximizes the probability of directional accuracy. As orders arrive during the day, the traders run the models, also called "solve the models," to generate short-term forecasts for stocks on their lists in step 505. When combined with impact cost estimates, these price forecasts allow the traders to better schedule their

executions. The outcome should be enhanced trading performance and lower transaction costs.

In step 506, comprehensive diagnostics indicate when and why the models work and don't work. By analyzing forecasting errors, information is accumulated suggesting new indicators and better transformations for existing ones. This feedback loop insures that the system will improve with time and experience.

Table 4Aand 4B illustrate how candidate variables are identified for the pool. The variables in Table 4A indicate example variables that are directly observable in at least one of the data sources available to a trader either from an exchange or from the trader's own program trades. These variables are grouped in the Table by whether the are most directly related to price, volume, depth or calendar events. Table 4B lists some of the operations that can be performed on the data to generate derived measurements from the data. Individually, these operations are known to those of ordinary skill in the art in the art. We consider performing any these operations on any of the observable variables in generating potential variables for inclusion in the pool. This collection of variables and transformation, however, is not believed to be routinely considered by other systems. With 12 transformation listed in Table 4B potentially operating on 13 observable variables, 12*13 = 156 potential variables can be generated for consideration just from the examples listed in Tables 4A and 4B.

Table 4A

Table 4C

Half-Hour Price Predictors		
Relative Strength Indicators	Lagged Returns on S&P Futures	
Trading Range Breakouts	Lagged Price Change in Stock Options	
Trading Range Locations	Price Volatility	
Stochastic Signals	Tic Volatility	
Moving Average Convergance Divergance	Volume Volatility	
Signals from Stochastic	Signals from Price & Volume Moves	
Moving Average Crossovers	Money Flow Trends (Uptick-Downtick Volume)	Money Flows
Lagged Returns on Related Stocks	Signals from Extreme Stochastic Levels	
	Signals from Extreme RSI Levels	
	Signals from Extreme Runs Levels	
	On-Balance Volume	

For the example of stocks in the universe of S&P 1500, the pooled variables fall into one of several classes. Continuous variables -- those with a value in every period -- should show *symmetric* forecasting power. This class of variable should forecast *both* up and down movements over 50% of the time. Signal variables -- those which equal 1 only when certain conditions are met -- are either bullish or bearish. When the signal is on, bullish (bearish) signals should predict up (down) moves with 65% reliability. To justify inclusion in the candidate pool, variables in this class should show significant forecasting power for *many* stocks. Specifically, the indicator should appear as a right hand side (RHS) variable in the final models of at least 5% of the stocks in the universe. For this to happen, the indicator must supply *independent* (non-redundant) forecasting power across a band cross-section stocks. The indicator's forecasting power should hold up through time. To evaluate its

stability, we test the indicator in three non-overlapping periods. For inclusion in the pool, it should show forecasting power for large numbers of stocks in all three time periods. Robustness through time is the true litmus test of forecasting accuracy -- it is also the most difficult condition to meet. The statistical properties of candidate indicators should resemble those of the dependent variable, half-hour stocks returns. Accordingly, the indicator's mean should be close to zero; its skewness close to zero; and its kurtosis close to three (tails to distribution). If these properties do not hold, it may be necessary to reconsider inclusion of the variable.

Figure 5C and 5D show reports generated as a result of the process shown in Figure 5B for the example of stock for GTE in one sliding window of samples. In Figure 5C, several derived variables based on GTE stock transactions on the exchange are plotted against half hour trading periods over several days on time axis 515. GTE Price, curve 511 and S&P 500 price, curve 512, are plotted on price axis 510. Dollar volume for GTE stock is hown by height o bars 521 using dollar volume axis 520. Indicators RSI, curve 533, Fast %K curve 532, and smoothed %D curve 531, are plotted using Indicator value axis 530. MACD, curve 541, and signal Line curve 542 are plotted using the MACD axis 540. some features on these curve, selected in step 502, show visual relationships to features in price, lending confidence to the objective methods that selected them. It is also evident that some curves, such as curves 541 and 5432 are similar enough to each other that they would not both be expected to be part of the best subset selected in step 503.

Figure 5D, shows a textual report produced at this stage of the processing. The data making up the sample are described in section 5using terms defined herein or known to those in the art. The best subset of candidate variables is listed in separate rows in column 561 of

section 560 of the report. Individual statistical relationships to price are shown in columns 562 through 564. The variables used in the OLS model have OLS coefficients or weights listed in column 565. The variables used by PROBIT are have their PROBI coefficients or weights listed in column 566. The value of the variable in the current half hour period is listed in column 567. In section 570, the results of the price return predictions in the example are presented. Of 19 variables considered in column 571, five predict an increase in price (bullish) and seven predict a downward change (bearish). Of the seven variables used by the OLS model, three are listed as bullish and two are listed as bearish in column 572. Of the nine variables used by PROBIT, four are bullish and two are bearish in column 573. In column 574, OLS predicts a downward price return of .01% in the next half hour period. In column 576, PROBIT predicts a 68% probability of a downward price return in the next half hour(with a 23% chance the down change is "Big"); and a residual, 32% chance that the next half hour will produce an increase in price.

DECISION SUPPORT SYSTEM

The forecasts of transaction costs are useful to traders in deciding whether and when to trade The predictions can be rolled up and averaged over a portfolio of stocks and a program of trade orders. In one embodiment this information is presented in a report that can be selectively printed out or displayed on a screen at the user's discretion. Figure 6A and 6B depict the left and right portions of this report for a sample portfolio trade. The components of transaction cost are presented on the last five lines of Figure 6B.

The computation and reporting of transaction cost or its component impact cost or trend cost are concrete, useful and tangible results. Because these results are accepted by traders and relied upon in subsequent trades.

AUTOMATED TRADING WITH MINIMUM TRANSACTION COSTS

The data ingest and model parameter fits and predictions using the model are performed in some embodiments using a digital computer as depicted in Figure 2. The transaction cost predictions can be used iteratively to find a value for the urgency quotient that minimizes transaction costs. Alternatively, a transaction cost can be found that is below a threshold value selected by or for the trader.

In one embodiment the computer is programmed to vary the urgency quotient from 0 to 1 in small increments, for example, 0.05 in quotient value, and identify the optimal urgency quotient value at which the predicted transaction costs are a minimum. The program then devises a sequence of trades corresponding to the optimal urgency quotient and automatically initiates those trades, perhaps with a user indicating approval with a single click. The user's portfolio account information is then updated to reflect the consequences of the trades.

CONCLUSION

In the foregoing specification, the invention has been described with reference to specific embodiments thereof. It will, however, be evident that various modifications and changes may be made thereto without departing from the broader spirit and scope of the invention. The specification and drawings are, accordingly, to be regarded in an illustrative rather than a restrictive sense.

CLAIMS

What is claimed is:

1. A method for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the method comprising:

selecting measurements of transaction price and transaction volume and transaction time;

fitting a model for price to the selected measurements, the model including a term of the form βV^{δ} wherein V is a function of volume, to estimate values for β and δ; and

computing a predicted impact cost for a trade in response to βS^{δ} wherein S is responsive to a transaction size for the trade.

2. The method of claim 1, wherein said fitting a model further comprises

selecting one or more multiplicative variables from a set of candidate variables based on univariate statistics between volume and price, and

β is a function of the one or more multiplicative variables.

3. The method of claim 2, wherein the set of candidate variables include at least one of liquidity, liquidity volatility, price trend and price trend volatility.

4. The method of claim 2, wherein the set of candidate variables includes at least one cross sectional factor involving other items traded on the exchange.

5. The method of claim 1, wherein said fitting a model further comprises

selecting one or more exponential variables from a set of candidate variables based on univariate statistics between a logarithm of volume and a logarithm of price, and

δ is a function of the one or more exponential variables.

6. The method of claim 5, wherein the set of candidate variables includes at least one of liquidity, liquidity volatility, price trend and price trend volatility.

7. The method of claim 1, wherein the model includes a term α independent of transaction volume.

8. The method of claim 1, wherein said fitting a model further comprises

selecting one or more additive variables from a set of candidate variables based on univariate statistics between each variable of the set of candidate variables and price, and

α is a function of the one or more additive variables.

9. The method of claim 8, wherein the set of candidate variables includes at least one of liquidity, liquidity volatility, price trend and price trend volatility.

10. The method of claim 1, further comprising presenting said impact cost for at least one of storage and display and a paper report.

11. The method of claim 1, further comprising computing a predicted transaction cost in response to the predicted impact cost.

12. The method of claim 1, further comprising initiating a trade in response to at least the predicted impact cost.

13. The method of claim 1, further comprising

proposing a trade to fill the order with at least one revised transaction size; and

returning to said computing the predicted impact cost until a predicted impact cost substantially equals at least one of a minimum impact cost and a value less than a threshold impact cost.

14. The method of claim 11, further comprising

proposing a trade to fill the order with at least one revised transaction size; and

returning to said computing the predicted impact cost until a predicted transaction cost substantially equals at least one of a minimum transaction cost and a value less than a threshold transaction cost.

15. The method of claim 1, wherein S is substantially equal to a trade size excess

16. The method of claim 1, wherein

said selecting measurements further comprises segregating measurements into measurement categories by a sign of signed volumes derived from said transaction volume measurements and transaction price measurements; and

said fitting the model further comprises fitting the model separately in each of the measurement categories.

17. The method of claim 1, further comprising:

computing a predicted trend cost; and

computing a predicted transaction cost responsive to the predicted impact cost and the predicted trend cost.

18. The method of claim 1, further comprising:

computing a predicted trend cost from an second model; and

computing a predicted transaction cost responsive to the predicted impact cost and the predicted trend cost.

19. The method of claim 18, said computing a predicted trend cost further comprising:

selecting model variables for the second model;

obtaining weights for the second model variables by fitting the second model to the measurements of transaction price; and

running the second model to generate real-time forecast of price trend; and

computing trend cost in response to the real-time forecast of price trend.

20. The method of claim 19, said computing a predicted trend cost further comprising building a pool of candidate variables before said selecting model variables.

21. The method of claim 20, said computing a predicted trend cost further comprising identifying a best subset of the pool of candidate variables before said selecting model variables.

22. The method of claim 20, said computing a predicted trend cost further comprising monitoring out-of-sample forecasting accuracy.

23. A method for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the method comprising:

receiving data indicating transactions on an exchange;

deriving measurements of transaction price and transaction volume and transaction time from said data;

computing a predicted price return for a time period based on the measurements;

computing a predicted transaction cost in response to the predicted price return.

24. The method of claim 23, wherein:

the method further comprises computing a predicted trend cost for a trade in response to the predicted price return; and

said computing the predicted transaction cost in response to the predicted trend cost.

25. The method of claim 23, said computing a predicted price return further comprising:

selecting model variables for a model;

obtaining weights for the model variables by fitting the model to the measurements of transaction price; and

running the model to generate a real-time forecast of price return.

26. The method of claim 25, said computing a predicted price return further comprising building a pool of candidate variables before said selecting model variables.

27. The method of claim 26, said computing a predicted price return further comprising identifying a best subset of the pool of candidate variables before said selecting model variables.

28. The method of claim 25, said computing a predicted price return further comprising monitoring out-of-sample forecasting accuracy.

29. A method for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the method comprising:

receiving data indicating transactions on an exchange;

deriving measurements of transaction price and transaction volume and transaction time from said data;

computing a predicted impact cost based on the measurements;

computing a predicted trend cost based on the measurements;

computing a predicted transaction cost in response to the predicted trend cost and the predicted impact cost.

30. The method of claim 29, said computing a predicted trend cost further comprising:

selecting model variables for model;

obtaining weights for model variables by fitting model to the measurements of transaction price; and

running model to generate real-time forecast of price trend; and

computing trend cost in response to the real-time forecast of price trend.

31. A method for deriving transaction costs of trades on an exchange directly from data available from the exchange, the method comprising:

receiving data indicating transactions on the exchange;

deriving measurements including a transaction price, a transaction volume, and a transaction time for each of a plurality of transactions from said data;

deriving an impact cost from the measurements;

deriving a trend cost from the measurements;

computing a transaction cost in response to the trend cost and the impact cost.

32. The method of claim 31, said deriving the impact cost comprising computing a difference between a price of a current transaction associated with a particular trade and a price of a transaction immediately preceding the current transaction.

33. The method of claim 32, said deriving the trend cost comprising computing a difference between a price change over the particular trade and the impact cost of the particular trade.

34. A method for deriving impact costs of trades on an exchange directly from measurements, the method comprising:

selecting measurements of transaction price and transaction volume and transaction time;

ordering the selected measurements temporally ;

determining whether a current transaction is part of a particular trade for which impact costs are to be measured;

if a current transaction is part of the particular trade, then

if a price difference from an immediately preceding transaction is in the same direction as the current transaction, associating with the current transaction an impact equal to the price difference;

if the current transaction is a last transaction in the particular trade, computing the impact cost as the volume weighted average of the one or more impacts associated with the one or more transaction from the particular trade.

35. The method of claim 34, before said computing the impact cost, said method further comprising:

if the current transaction is not part of the particular trade, then

if the current transaction is in the opposite direction of a prior transaction from the particular trade by an amount equal to or greater than the impact associated with the prior transaction, setting an impact associated with the prior transaction to zero.

36. An apparatus for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the apparatus comprising:

a computer readable medium;

one or more processors connected to the computer readable medium, the one or more processors configured to

select measurements of transaction price and transaction volume and transaction time;

fit a model for price to the selected measurements, the model including a term of the form βV^{δ} wherein V is a function of volume, to estimate values for β and δ; and

compute a predicted impact cost for a trade in response to βS^{δ} wherein S is responsive to a transaction size for the trade.

37. An apparatus for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the apparatus comprising:

a computer readable medium; and

one or more processors connected to the computer readable medium, the one or more processors configured to

receive data indicating transactions on an exchange

derive measurements of transaction price and transaction volume and transaction time from said data;

compute a predicted price return for a time period based on the measurements;

compute a predicted trend cost for a trade in response to the predicted price return; and

compute a predicted transaction in response to the predicted trend cost.

38. An apparatus for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the apparatus comprising:

a computer readable medium; and

one or more processors connected to the computer readable medium, the one or more processors configured to:

receive data indicating transactions on an exchange,

derive measurements of transaction price and transaction volume and transaction time from said data,

compute a predicted impact cost based on the measurements,

compute a predicted trend cost based on the measurements, and

compute a predicted transaction cost in response to the predicted trend cost and the predicted impact cost.

39. An apparatus for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the apparatus comprising::

a computer readable medium; and

one or more processors connected to the computer readable medium, the one or more processors configured to:

receive data indicating transactions on the exchange,

derive measurements including a transaction price, a transaction volume, and a transaction time for each of a plurality of transactions from said data,

derive an impact cost from the measurements,

derive a trend cost from the measurements and the impact cost, and

compute a transaction cost in response to the trend cost and the impact cost.

40. An apparatus for deriving impact costs of trades on an exchange directly from measurements, the apparatus comprising:

a computer readable medium; and

one or more processors connected to the computer readable medium, the one or more processors configured to

select measurements of transaction price and transaction volume and transaction time;

order the selected measurements temporally ;

determine whether a current transaction is part of a particular trade for which impact costs are to be measured;

if a current transaction is part of the particular trade, then

if a price difference from an immediately preceding transaction is in the same direction as the current transaction, associate with the current transaction an impact equal to the price difference; and

if the current transaction is a last transaction in the particular trade, compute the impact cost as the volume weighted average of the one or more impacts associated with the one or more transaction from the particular trade.

41. A computer program product for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the computer program product comprising:

a computer readable medium;

instructions stored on the computer readable medium to cause one or more processors to

select measurements of transaction price and transaction volume and transaction time;

fit a model for price to the selected measurements, the model including a term of the form βV^{δ} wherein V is a function of volume, to estimate values for β and δ; and

compute a predicted impact cost for a trade in response to βS^{δ} wherein S is responsive to a transaction size for the trade.

42. A computer program product for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the computer program product comprising:

a computer readable medium; and

instructions stored on the computer readable medium to cause one or more processors to

receive data indicating transactions on the exchange;

derive measurements of transaction price and transaction volume and transaction time from said data;

compute a predicted price return for a time period based on the measurements;

compute a predicted trend cost for a trade in response to the predicted price return; and

compute a predicted transaction cost in response to the predicted trend cost.

43. A computer program product for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the computer program product comprising:

a computer readable medium; and

instructions stored on the computer readable medium to cause one or more processors to:

receive data indicating transactions on an exchange,

derive measurements of transaction price and transaction volume and transaction time from said data,

compute a predicted impact cost based on the measurements,

compute a predicted trend cost based on the measurements, and

compute a predicted transaction cost in response to the predicted trend cost and the predicted impact cost.

44. A computer program product for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the computer program product comprising:

a computer readable medium; and

instructions stored on the computer readable medium to cause one or more processors to;

receive data indicating transactions on the exchange,

derive measurements including a transaction price, a transaction volume, and a transaction time for each of a plurality of transactions from said data,

derive an impact cost from the measurements,

derive a trend cost from the measurements and the impact cost, and

compute a transaction cost in response to the trend cost and the impact cost.

45. A computer program product for deriving impact costs of trades on an exchange directly from measurements, the computer program product comprising:

a computer readable medium; and

instructions stored on the computer readable medium for causing one or more processors to

select measurements of transaction price and transaction volume and transaction time;

order the selected measurements temporally ;

determine whether a current transaction is part of a particular trade for which impact costs are to be measured;

if a current transaction is part of the particular trade, then

if a price difference from an immediately preceding transaction is in the same direction as the current transaction, associate with the current transaction an impact equal to the price difference; and

if the current transaction is a last transaction in the particular trade, compute the impact cost as the volume weighted average of the one or more impacts associated with the one or more transaction from the particular trade.

46. A decision aid system for predicting transaction costs in filling an order having an order size for a particular item by one or more trades on an exchange, the system comprising:

a network;

a computer readable medium connected to the network; and

one or more processors connected to the network, the one or more processors configured to

receive data over the network indicating transactions on an exchange;

derive measurements of transaction price and transaction volume and transaction time;

compute a predicted price return for a time period based on the selected measurements; and

compute a predicted transaction cost in response to the predicted price return.

47. The decision aid system of claim 46 the one or more processors further configured to:

compute a predicted trend cost for a trade in response to the predicted price return; and

compute the predicted transaction in response to the predicted trend cost.

48. The decision aid system of claim 46 the one or more processors further configured to:

compute a predicted impact cost for a trade in response to the predicted price return; and

compute the predicted transaction in response to the predicted impact cost.

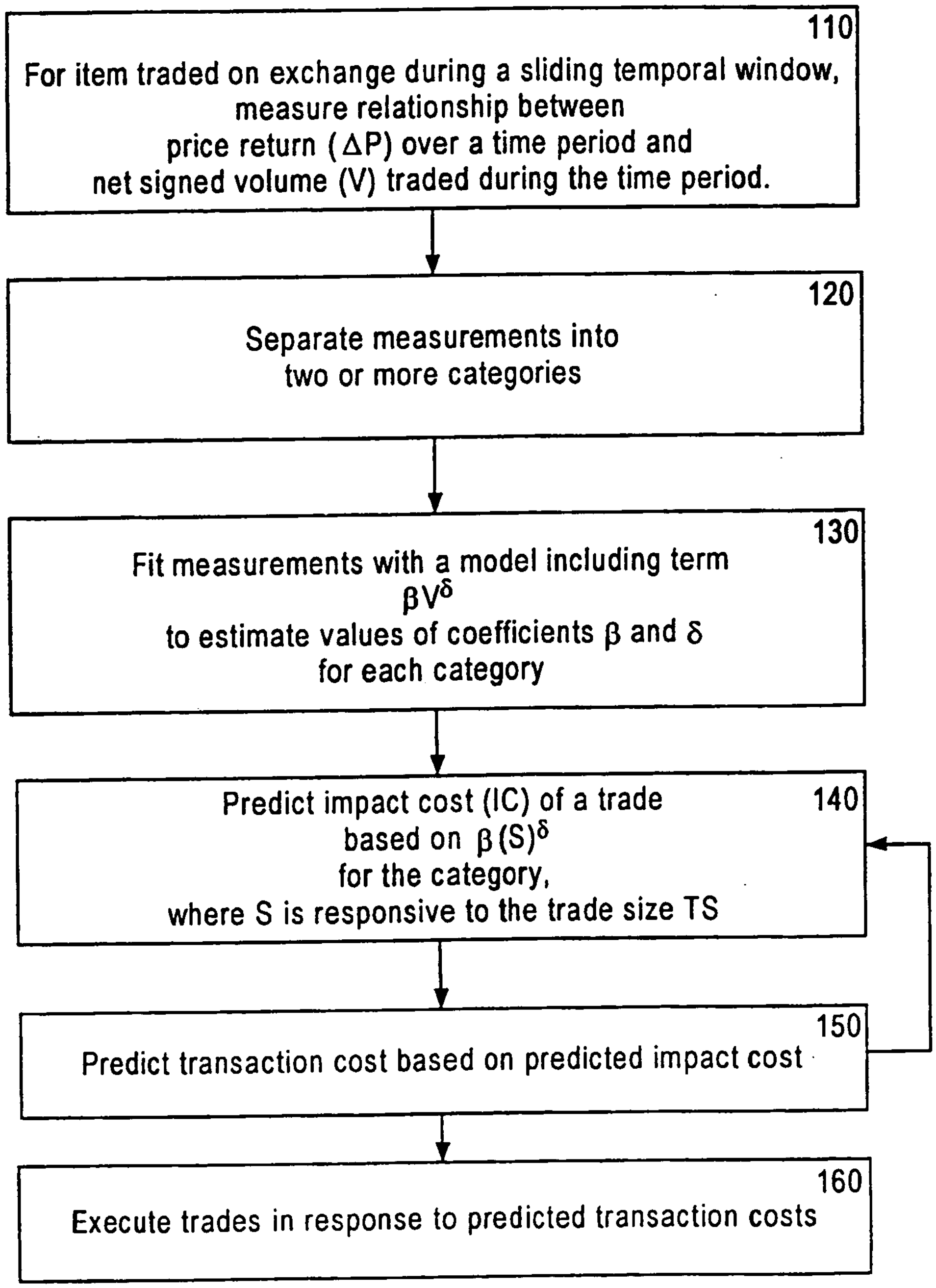

110
For item traded on exchange during a sliding temporal window, measure relationship between price return (ΔP) over a time period and net signed volume (V) traded during the time period.
120
Separate measurements into two or more categories
130
Fit measurements with a model including term βV^{δ} to estimate values of coefficients β and δ for each category
140
Predict impact cost (IC) of a trade based on $\beta (S)^{\delta}$ for the category, where S is responsive to the trade size TS
150
Predict transaction cost based on predicted impact cost
160
Execute trades in response to predicted transaction costs

FIG. 1

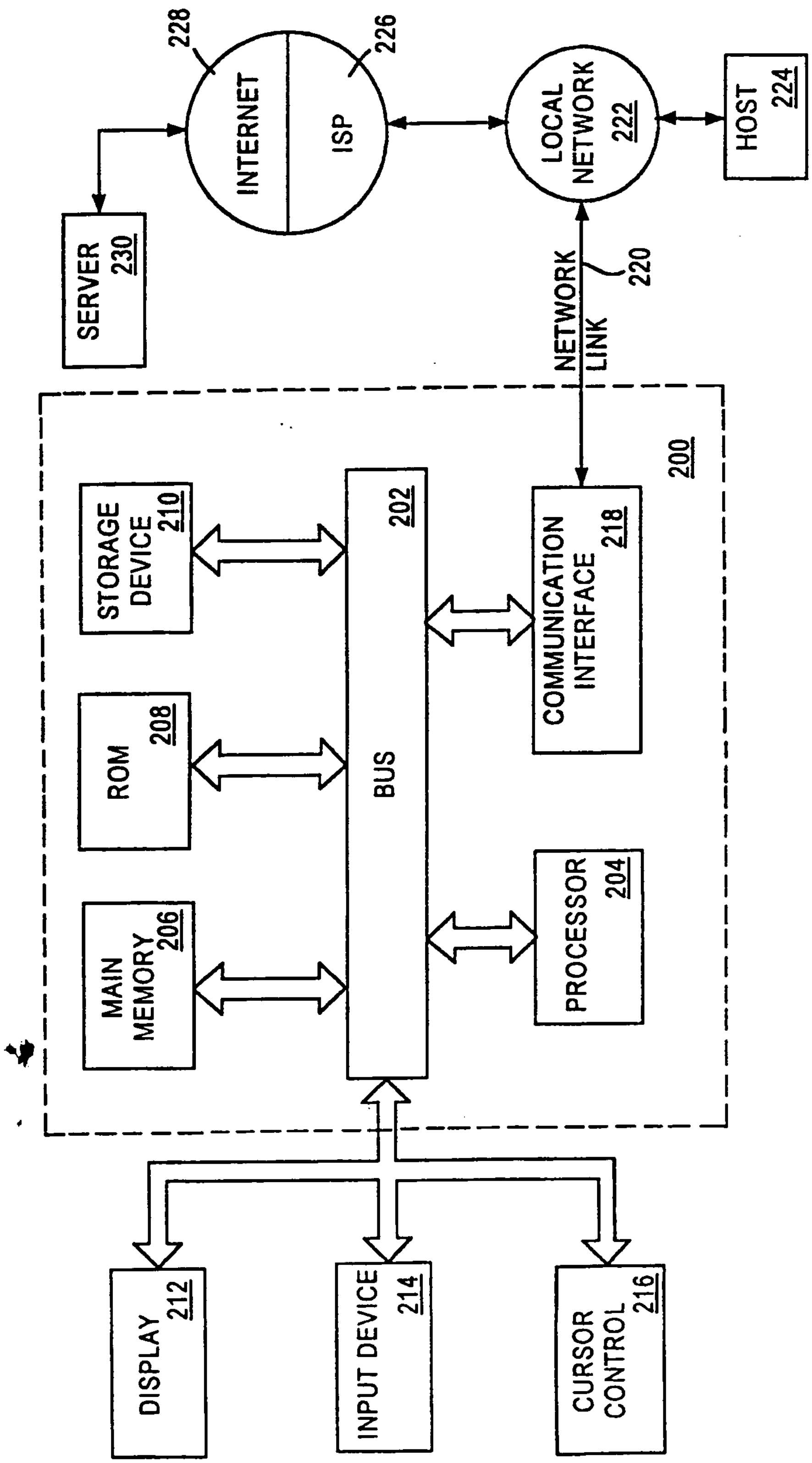

INTERNET
228
ISP
226
LOCAL NETWORK
222
HOST
224
SERVER
230
NETWORK LINK
220
200
STORAGE DEVICE
210
ROM
208
MAIN MEMORY
206
BUS
202
COMMUNICATION INTERFACE
218
PROCESSOR
204
DISPLAY
212
INPUT DEVICE
214
CURSOR CONTROL
216

FIG. 2

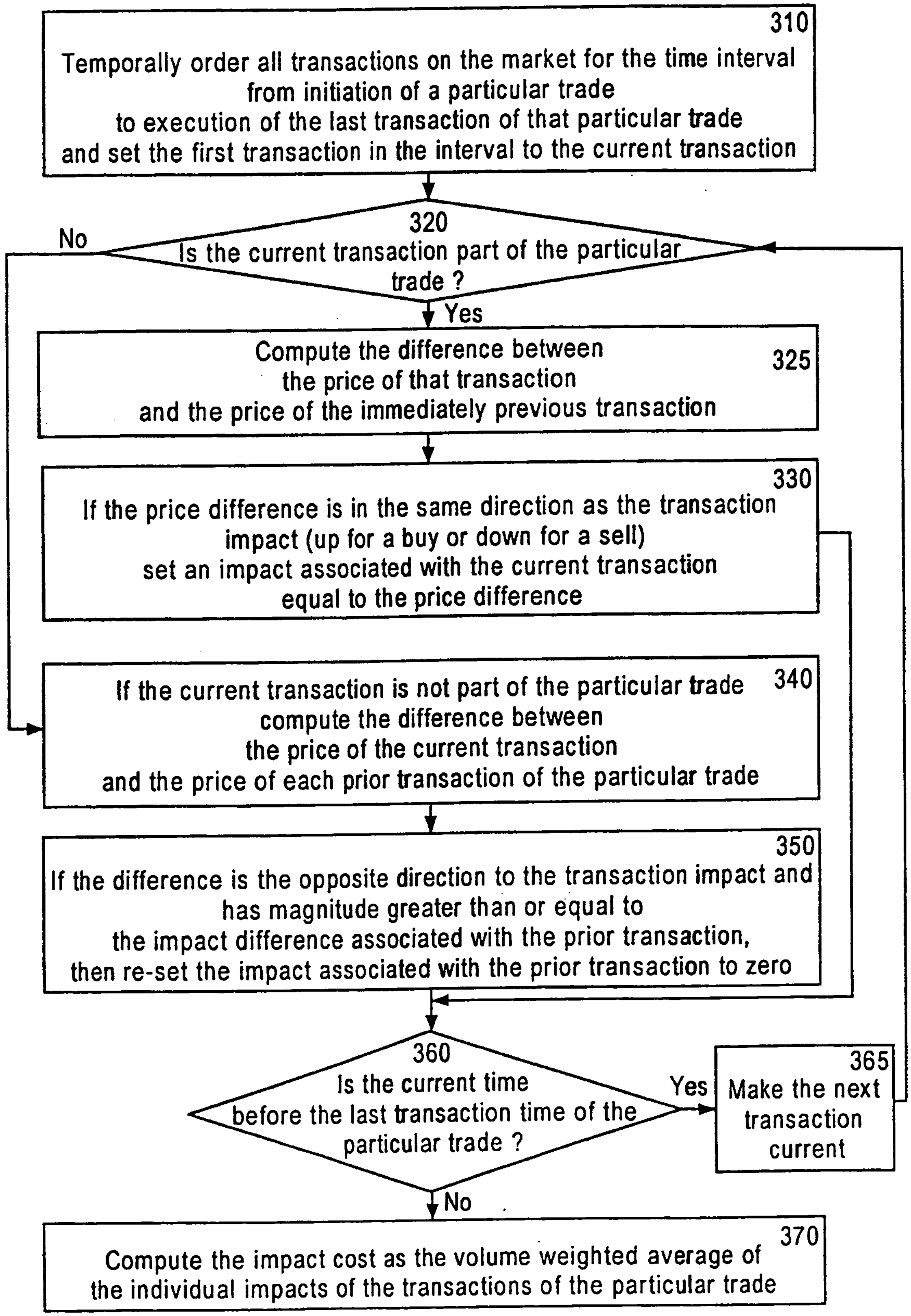

310
Temporally order all transactions on the market for the time interval from initiation of a particular trade to execution of the last transaction of that particular trade and set the first transaction in the interval to the current transaction
320
Is the current transaction part of the particular trade ?
No
Yes
Compute the difference between the price of that transaction and the price of the immediately previous transaction
325
330
If the price difference is in the same direction as the transaction impact (up for a buy or down for a sell) set an impact associated with the current transaction equal to the price difference
If the current transaction is not part of the particular trade compute the difference between the price of the current transaction and the price of each prior transaction of the particular trade
340
350
If the difference is the opposite direction to the transaction impact and has magnitude greater than or equal to the impact difference associated with the prior transaction, then re-set the impact associated with the prior transaction to zero
360
Is the current time before the last transaction time of the particular trade ?
Yes
365
Make the next transaction current
No
370
Compute the impact cost as the volume weighted average of the individual impacts of the transactions of the particular trade

FIG. 3A

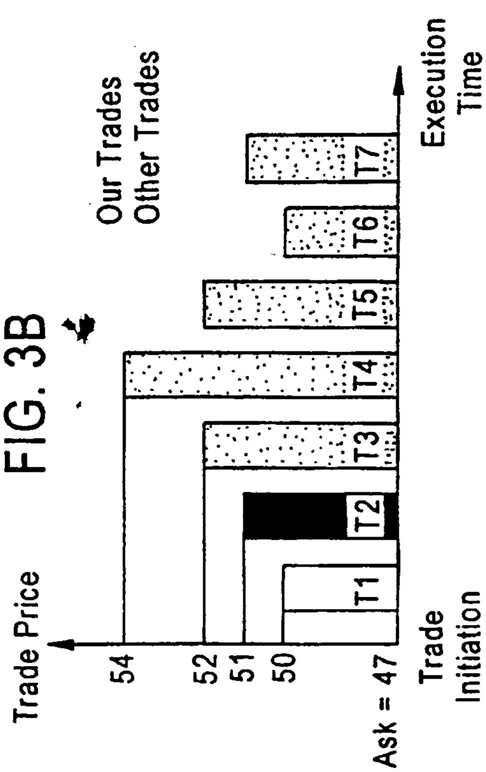


FIG. 3B

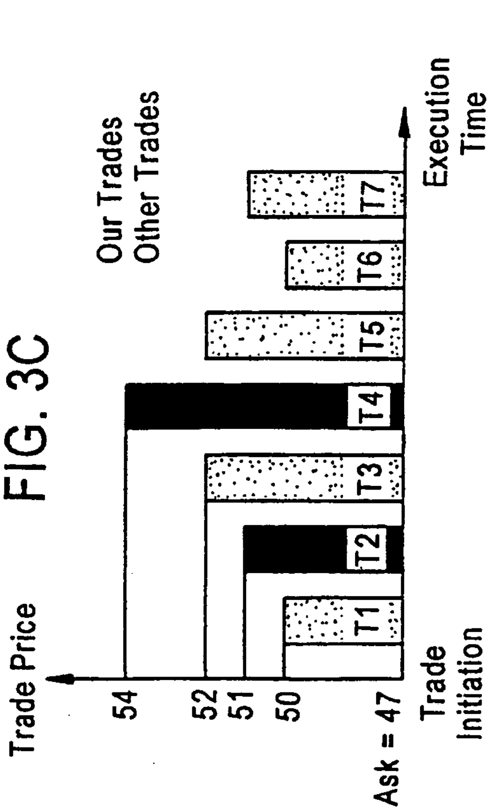


FIG. 3C

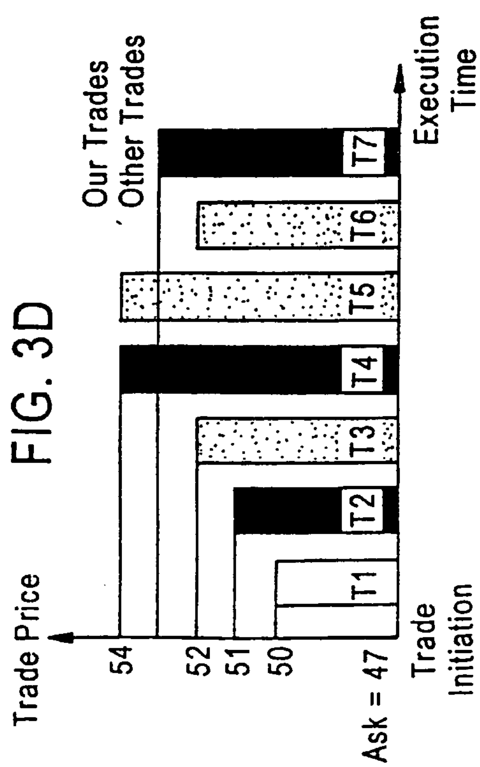


FIG. 3D

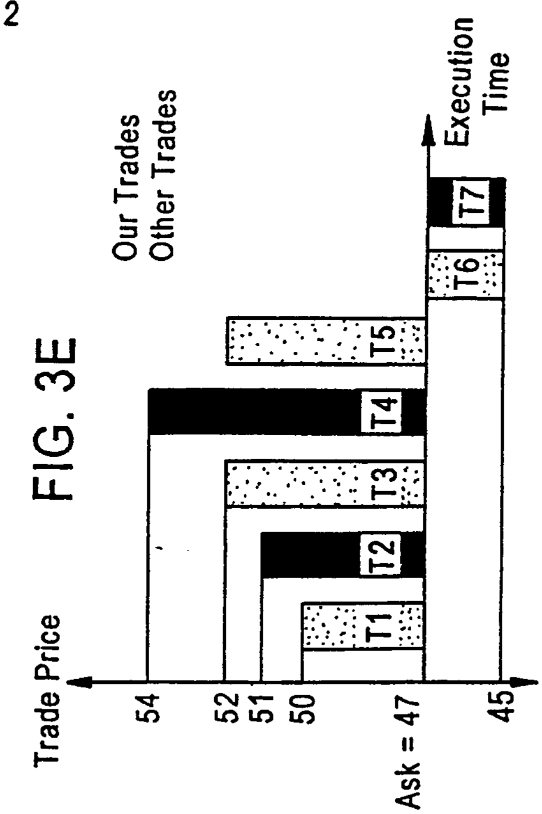


FIG. 3E

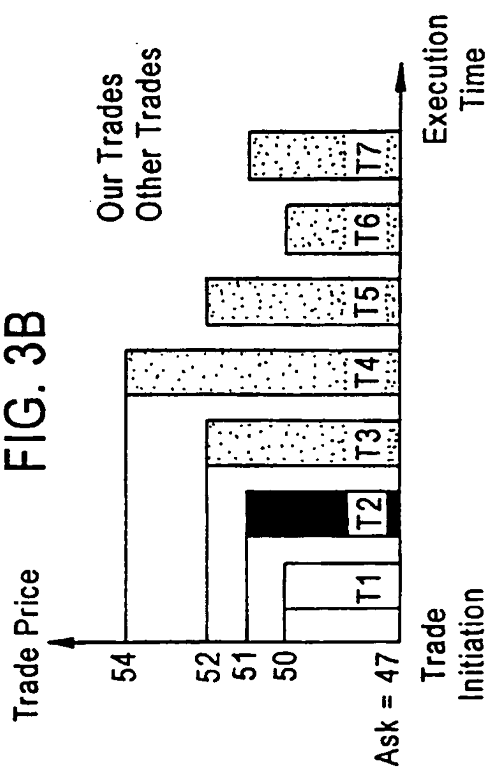


FIG. 3B

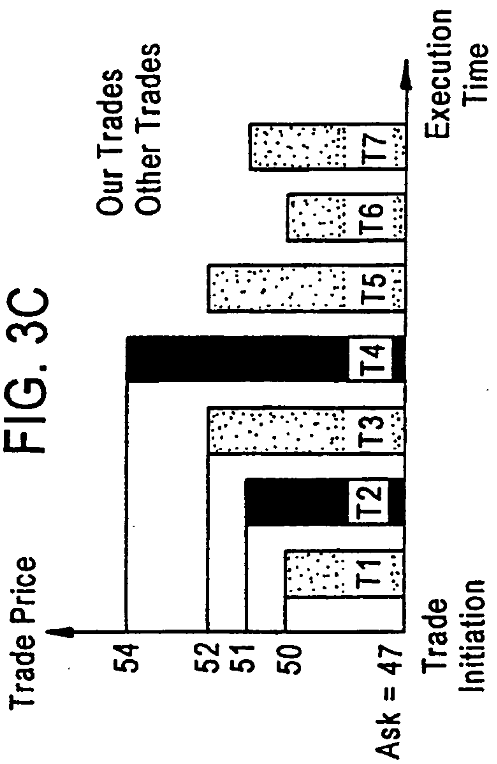


FIG. 3C

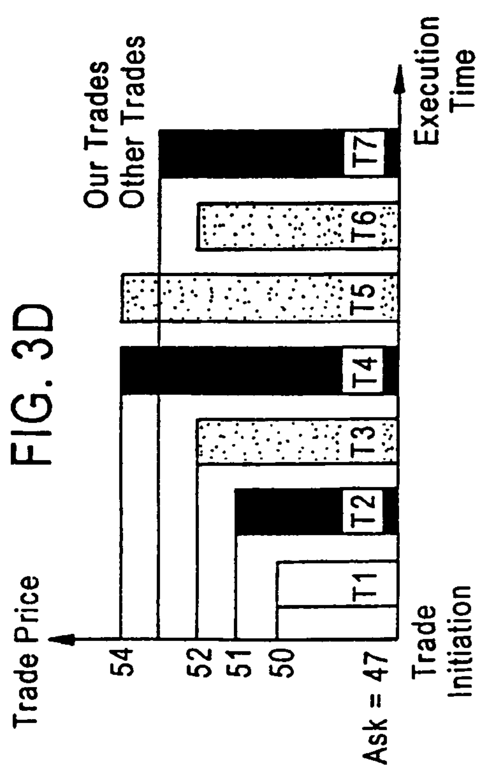


FIG. 3D

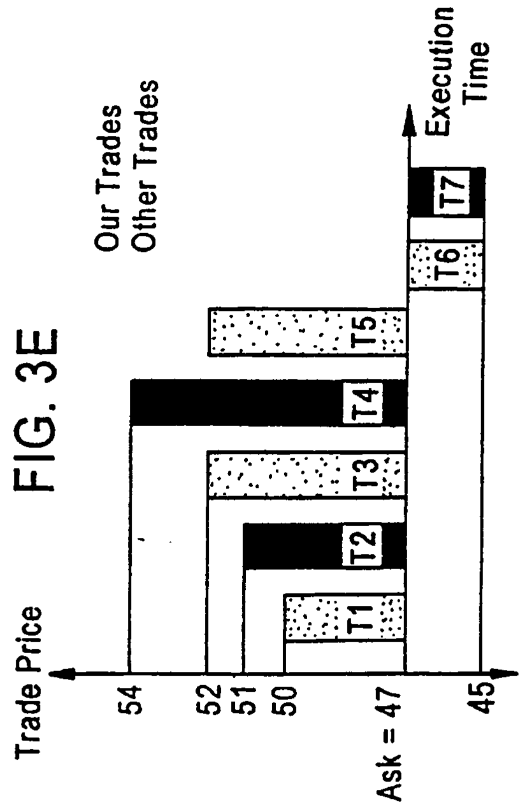


FIG. 3E

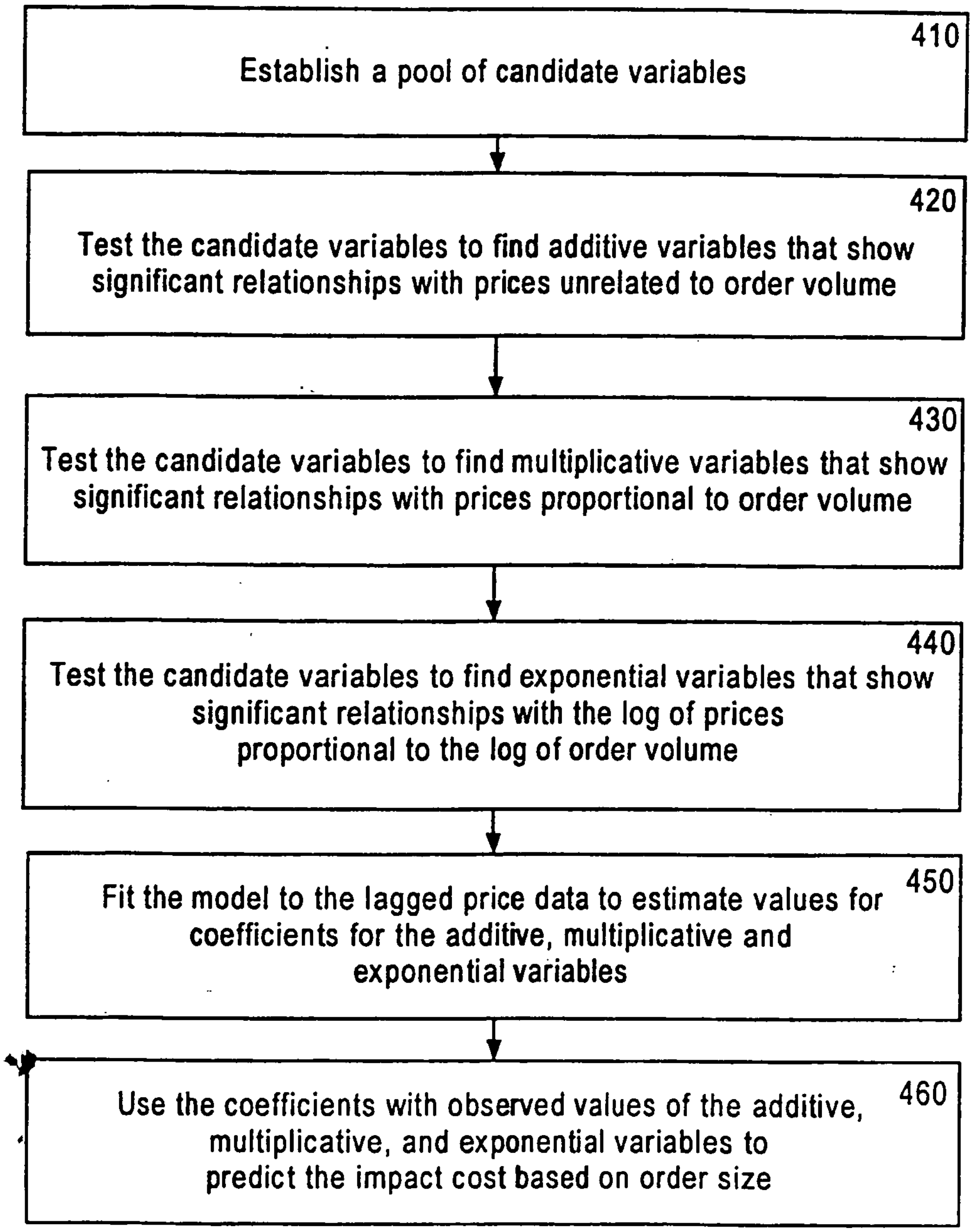

410
Establish a pool of candidate variables
420
Test the candidate variables to find additive variables that show significant relationships with prices unrelated to order volume
430
Test the candidate variables to find multiplicative variables that show significant relationships with prices proportional to order volume
440
Test the candidate variables to find exponential variables that show significant relationships with the log of prices proportional to the log of order volume
450
Fit the model to the lagged price data to estimate values for coefficients for the additive, multiplicative and exponential variables
460
Use the coefficients with observed values of the additive, multiplicative, and exponential variables to predict the impact cost based on order size

FIG. 4A

6/12

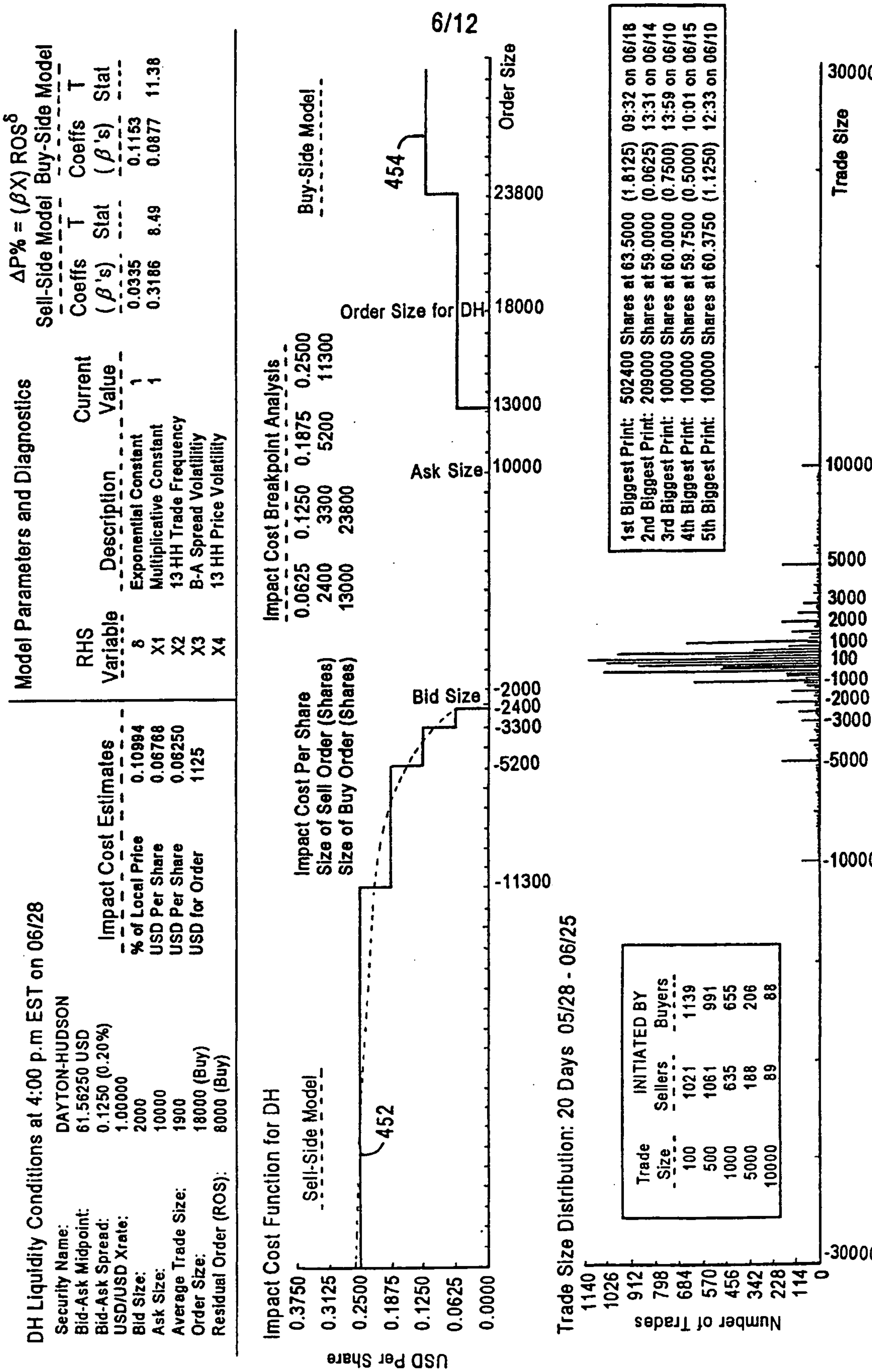

DH Liquidity Conditions at 4:00 p.m EST on 06/28
Security Name: DAYTON-HUDSON
Bid-Ask Midpoint: 61.56250 USD
Bid-Ask Spread: 0.1250 (0.20%)
USD/USD Xrate: 1.00000
Bid Size: 2000
Ask Size: 10000
Average Trade Size: 1900
Order Size: 18000 (Buy)
Residual Order (ROS): 8000 (Buy)
Impact Cost Estimates
% of Local Price 0.10994
USD Per Share 0.06768
USD Per Share 0.06250
USD for Order 1125
Model Parameters and Diagnostics
RHS Variable Description Current Value
δ Exponential Constant 1
X1 Multiplicative Constant 1
X2 13 HH Trade Frequency
X3 B-A Spread Volatility
X4 13 HH Price Volatility
ΔP% = (βX) ROS^δ
Sell-Side Model Coeffs (β's) T Stat
0.0335
0.3186 8.49
Buy-Side Model Coeffs (β's) T Stat
0.1153
0.0877 11.38
Impact Cost Function for DH
Sell-Side Model
Buy-Side Model
Impact Cost Per Share
Size of Sell Order (Shares)
Size of Buy Order (Shares)
Impact Cost Breakpoint Analysis
0.0625 0.1250 0.1875 0.2500
2400 3300 5200 11300
13000 23800
USD Per Share
0.3750 0.3125 0.2500 0.1875 0.1250 0.0625 0.0000
452
454
Bid Size
Ask Size
Order Size for DH
Order Size
-11300 -5200 -3300 -2400 -2000 10000 13000 18000 23800
Trade Size Distribution: 20 Days 05/28 - 06/25
Number of Trades
1140 1026 912 798 684 570 456 342 228 114 0
Trade Size
-30000 -10000 -5000 -3000 -2000 -1000 100 1000 2000 3000 5000 10000 30000
Trade Size | INITIATED BY Sellers | Buyers
100 1021 1139
500 1061 991
1000 635 655
5000 188 206
10000 89 88
1st Biggest Print: 502400 Shares at 63.5000 (1.8125) 09:32 on 06/18
2nd Biggest Print: 209000 Shares at 59.0000 (0.0625) 13:31 on 06/14
3rd Biggest Print: 100000 Shares at 60.0000 (0.7500) 13:59 on 06/10
4th Biggest Print: 100000 Shares at 59.7500 (0.5000) 10:01 on 06/15
5th Biggest Print: 100000 Shares at 60.3750 (1.1250) 12:33 on 06/10

FIG. 4B

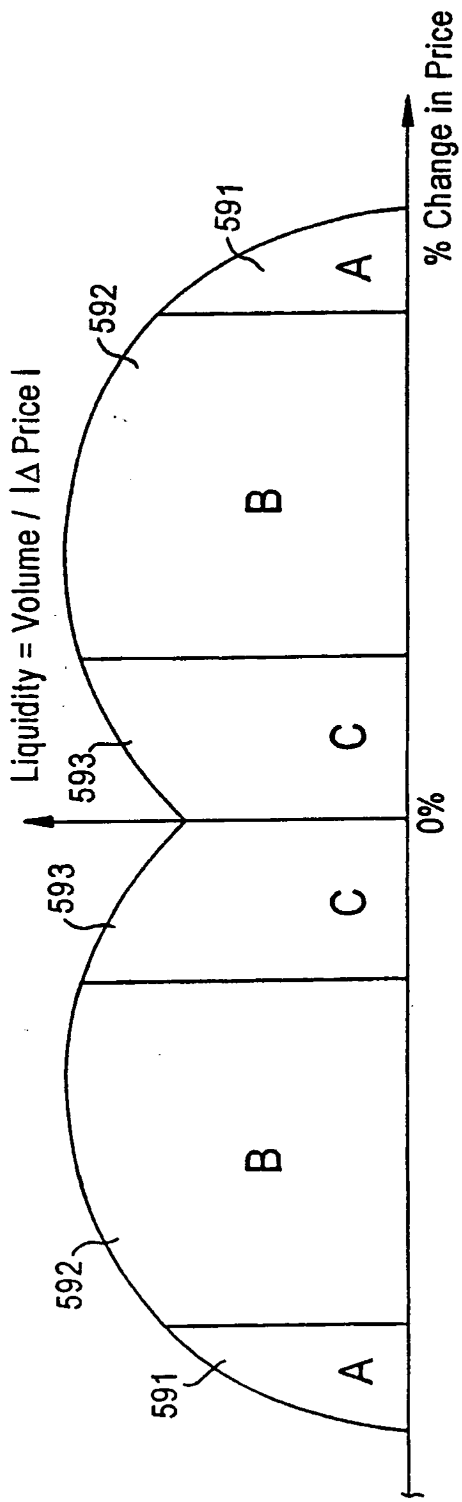

Liquidity = Volume / I∆ Price I
% Change in Price
0%
A
B
C
C
B
A
591
592
593
593
592
591

FIG. 5A

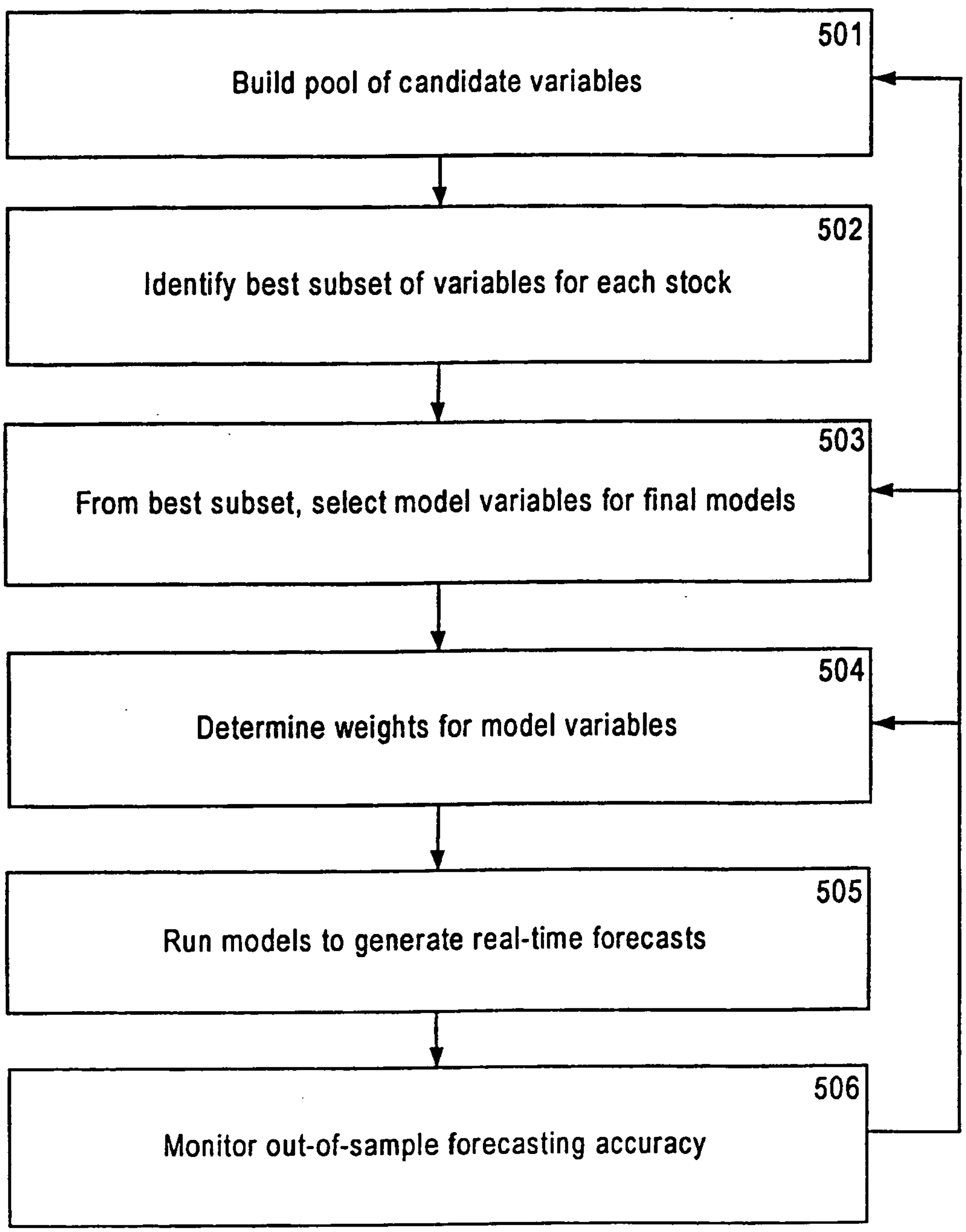
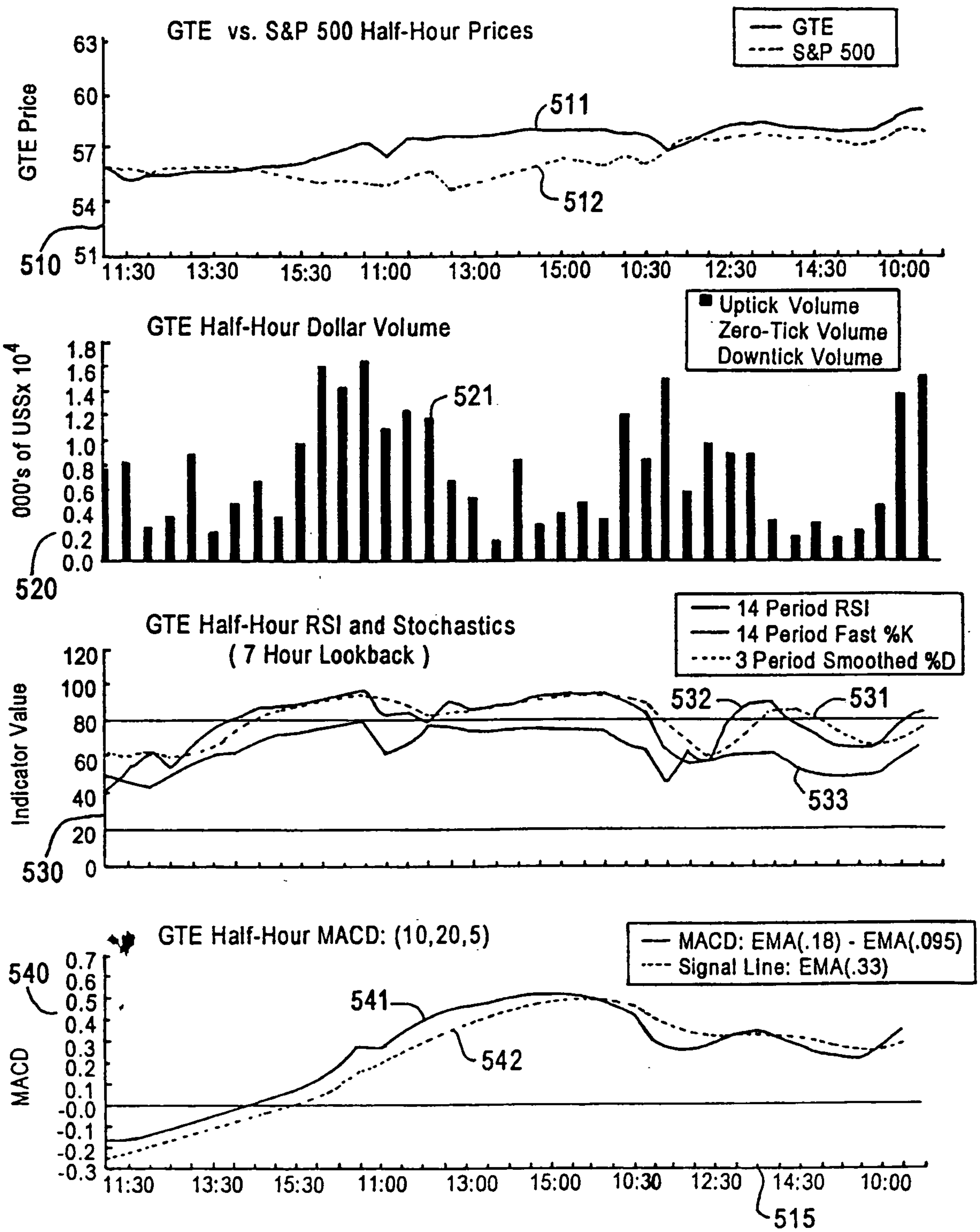

501
Build pool of candidate variables
502
Identify best subset of variables for each stock
503
From best subset, select model variables for final models
504
Determine weights for model variables
505
Run models to generate real-time forecasts
506
Monitor out-of-sample forecasting accuracy

FIG. 5B



GTE vs. S&P 500 Half-Hour Prices
GTE
S&P 500
GTE Price
63
60
57
54
51
511
512
510
11:30
13:30
15:30
11:00
13:00
15:00
10:30
12:30
14:30
10:00
GTE Half-Hour Dollar Volume
Uptick Volume
Zero-Tick Volume
Downtick Volume
000's of US$x 10^4
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
521
520
GTE Half-Hour RSI and Stochastics
(7 Hour Lookback)
14 Period RSI
14 Period Fast %K
3 Period Smoothed %D
Indicator Value
120
100
80
60
40
20
0
532
531
533
530
GTE Half-Hour MACD: (10,20,5)
MACD: EMA(.18) - EMA(.095)
Signal Line: EMA(.33)
540
MACD
0.7
0.6
0.5
0.4
0.3
0.2
0.1
-0.0
-0.1
-0.2
-0.3
541
542
515

FIG. 5C

Back To Main

Donaldson, Lufkin & Jenrette
Summary Trade Profile
Pre-Trade Analytics

Client:	0	Portfolio Manager:	0	Ph
Account:	0	Trader:	0	

TRADE PROFILE

Exchg	Buys	Sells	Total	Buys	Sells	Total
NYSE	24	21	45	$30,274,663	$12,717,431	$42,992,094
AMEX	0	0	0	$0	$0	$0
OTC	0	0	0	$0	$0	$0
OTC AGENCY	2	5	7	$753,250	$13,072,613	$13,825,862
Total	26	26	52	$31,027,913	$25,790,044	$56,817,956

S&P 500 DEC FUTURE
RUSSELL 2000 DEC FUTURE
NYSE COMPSITE DEC FUTU

Tracking Error: Last 04 Weeks
Tracking Error: Next 04 Weeks
Tracking Error: Next 52 Weeks
52 Week R Squared (R^2)

SECTOR & INDUSTRY WEIGHTS

Secter	B	S	Highest Industry Weights	B	S
FINANCIAL	29	7	FINANCIAL (DIVERSIFIED)	29	6
CAPITAL GOODS	2	18	MACHINERY (DIVERSIFIED)	0	17
TECHNOLOGY	2	7	HOUSEHOLD PRODUCTS	4	0
CONSUMER STAPLE	5	0	ELECTRONICS (SEMICNDCTR)	0	4
CONSUMER CYCLCL	3	1	HEALTH CARE (DRUGS)	3	0
HEALTH CARE	3	1	RETAIL (BUILDING SUPPLY)	2	0
ENERGY	0	1	COMPUTERS (HARDWARE)	0	2
COMMUNICATIONS	9	9	COMPUTERS (SOFTWARE/SRY)	2	0
BASIC INDUSTRY	1	1	OIL DRILLING/EQUIPMENT	0	1
UTILITIES	0	0	ELECTRICAL EQUIPMENT	0	1

PRINCIPAL VALUE

Net $	$5,237,
Total $	$56,817

Portfolio is Most Sensitive
to the Following Indexes

PSE TECHNOLOGY INDEX
RUSSELL 3000 INDEX
S&P HEAVY TRUCKS & PA
S&P FOODS

LIQUIDITY % MOMENTUM

B-A Spread / Price	4	3/20 Day Price Ratio	3
05 Day Volume / Shso	6	5/45 Day On-Balance Volm	7
20 Day Volume / Shso	6	10 Day Trend Line Slope	4
20 Day Volume / 0	2	1/45 Week Price Ratio	4
Markt Capitalization	2	10/45 Day Volume ratio	5
Liquidity Score	4	*Momentum Score*	5
(1 = Max Liquidity)		*(1 = Max Favorable Momentum)*	

Component
Bid-Ask Sprd
Commissions
Price Trend
Trade Impact
Cost Estimate

FIG. 6A

Donaldson, Lufkin & Jenrette
Summary Trade Profile
Pre-Trade Analytics

0		Phone: (000) 000-0000	Received:		12/10/97 22:11
0		Fax: (000) 000-0000	Benchmark:		S&P 500 INDEX

OPTIMAL FUTURES HEDGES

Sells	Total					
		S&P 500 DEC FUTURE	905.96	7	-29	476
		RUSSELL 2000 DEC FUTURE	423.44		149	255
17,431	$42,992,094	NYSE COMPSITE DEC FUTURE	476.93			-1,112
$0	$0					
$0	$0	Tracking Error: Last 04 Weeks (%)		13.11%	9.39%	9.04%
72,613	$13,825,862	Tracking Error: Next 04 Weeks(%)		3.58%	3.43%	3.05%
90,044	$56,817,956	Tracking Error: Next 52 Weeks (%)		12.92%	12.36%	10.99%
		52 Week R Squared (R^2)		0	11	31

RISK ANALYSIS

B	S	PRINCIPAL VALUE					52 Week σ	52W Beta	4W Return
29	6	Net $	$5,237,869				139.09%	-0.64	146.55%
0	17	Total $	$56,817,956				12.82%	-0.06	13.51%
4	0								
0	4								
3	0	Portfolio Is Most Sensitive							
2	0	to the Following Indexes		σ Exp	52W Beta	1 % Rise ($)	B-S (%)	B+S (%)	
0	2	PSE TECHNOLOGY INDEX		35.00%	-0.39	-$220,854.00	-4.22%	-0.39%	
2	0	RUSSELL 3000 INDEX		28.00%	-0.10	-$59,236.00	-1.13%	-0.10%	
0	1	S&P HEAVY TRUCKS & PARTS		6.00%	-0.18	-$103,030.00	-1.97%	-0.18%	
0	1	S&P FOODS		6.00%	0.08	$47,363.00	0.90%	0.08%	

ESTIMATED TRANSACTION COSTS

	Component	Buys	Sells	Total	Buys	Sells	Total
3							
7	Bid-Ask Sprd	0.12	0.10	0.11	22.14	24.27	23.11
4	Commissions	0.00	0.00	0.00	0.00	0.00	0.00
4	Price Trend	0.00	0.00	0.00	0.00	0.00	0.00
5	Trade Impact	0.00	0.00	0.00	0.00	0.00	0.00
5	*Cost Estimate*	0.12	0.10	0.11	22.14	24.27	23.11

FIG. 6B

(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

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(25) Filing Language: English

(26) Publication Language: English

(30) Priority Data:
60/118,787 5 February 1999 (05.02.1999) US

(71) Applicant *(for all designated States except US)*: DLJ LONG TERM INVESTMENT CORPORATION [US/US]; Suite 1700, 200 West Madison Street, Chicago, IL 60606 (US).

(72) Inventors; and
(75) Inventors/Applicants *(for US only)*: COX, Berry [US/US]; Apartment 10 A, 25 East 86th Street, New York, NY 10028 (US). SARGENT, Tim [US/US]; 1265 Marls Court, Naperville, IL 60563 (US).

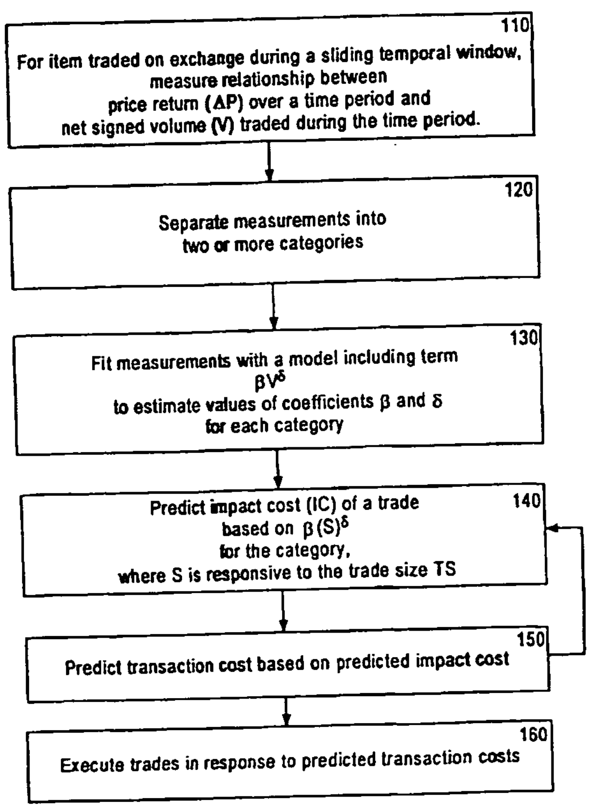
(74) Agents: MOLINELLI, Eugene, J. et al.; McDermott, Will & Emery, 600 13th Street, N.W., Washington, DC 20005-3096 (US).

(81) Designated States *(national)*: AE, AL, AM, AT, AU, AZ, BA, BB, BG, BR, BY, CA, CH, CN, CR, CZ, DE, DK, DM, EE, ES, FI, GB, GD, GE, GH, GM, HR, HU, ID, IL, IN, IS, JP, KE, KG, KR, KZ, LC, LK, LR, LS, LT, LU, LV, MA, MD, MG, MK, MN, MW, MX, NO, NZ, PL, PT, RO, RU, SD, SE, SG, SI, SK, SL, TJ, TM, TR, TT, TZ, UA, UG, US, UZ, VN, YU, ZA, ZW.

(84) Designated States *(regional)*: ARIPO patent (GH, GM, KE, LS, MW, SD, SL, SZ, TZ, UG, ZW), Eurasian patent (AM, AZ, BY, KG, KZ, MD, RU, TJ, TM), European patent (AT, BE, CH, CY, DE, DK, ES, FI, FR, GB, GR, IE, IT, LU, MC, NL, PT, SE), OAPI patent (BF, BJ, CF, CG, CI, CM, GA, GN, GW, ML, MR, NE, SN, TD, TG).

[Continued on next page]

(54) Title: TECHNIQUES FOR MEASURING TRANSACTION COSTS AND SCHEDULING TRADES ON AN EXCHANGE



(57) Abstract: Techniques predict transaction costs in filling an order by one or more trades on an exchange. Data indicating past transactions on an exchange are received. Measurements of transaction price and transaction volume and transaction time are derived from the data (110). A predicted price return for a time period is computed based on the measurements (110). Then a predicted transaction cost is computed in response to the predicted price return (150), for use in deciding whether to trade and for use in scheduling trades (160).

WO 00/46714 A3

INTERNATIONAL SEARCH REPORT

International application No.
PCT/US00/02692

A. CLASSIFICATION OF SUBJECT MATTER

IPC(7) : GO6F 17/60
US CL : 705/36, 37
According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

U.S. : 705/36, 37

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

Please See Extra Sheet.

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
	Please See Continuation of Second Sheet.	

[X] Further documents are listed in the continuation of Box C. [ ] See patent family annex.

* Special categories of cited documents

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"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

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"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
21 JUNE 2000	08 AUG 2000

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